Characterizing and Classifying Acoustical Ambient Sound Profiles

THESIS

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CHARACTERIZING AND CLASSIFYING ACOUSTICAL AMBIENT SOUND PROFILES

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Abstract

Acoustical modeling focuses on the sound pressures generated by the operation of some system of interest, the propagation of the sound through some medium (the atmosphere) and the sound pressure levels picked up by the receiver (listening device or a human). Ambient noise, or the background noise occurring naturally in an environment, affects the ability of the receiver to identify the sound from the system of interest. This work examines nominal logistic modeling of human performance data, methods to remove the time-dependency aspect of ambient sound profiles, and develops a method with which to classify sample ambient noise profiles against one of nine standard ambient noise profiles. The application of these methods to a notional scenario is provided.

This thesis is dedicated to my folks.

Acknowledgements

I would like to thank Dr. Hill for providing me with the proper tools and ideas necessary to complete my thesis as well as constantly maintaining a positive attitude throughout the process, which I was able to gain strength from and made my time at AFIT a lot more enjoyable. I would also like to thank my sponsors, Mr. John Hall and especially Dr. Frank Mobley at the 711th Human Performance Wing for constantly putting up with my data demands and questions despite a full work schedule and while teaching at Wright State University. Lastly, I would like to thank Dr. Stone for being a reader on this thesis and for giving me such a strong foundation in various OR skills that I learned while taking your classes.

Paul T. Gaski

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CHARACTERIZING AND CLASSIFYING ACOUSTICAL AMBIENT SOUND PROFILES

I. Introduction

Ambient noise, or the background noise that naturally occurs in an environment, plays a large part in the probability that an aircraft is perceived and heard by a human listener in that environment. Every unique environment in the world has its own ambient environment, an acoustic pattern that differs from all others. Although ambient noise is not the sole determining factor regarding whether or not an aircraft is heard by an observer, increasing our understanding of how ambient noise affects human hearing will lead to better capabilities in acoustic modeling that predicts if a stimulus is heard by a human observer. There are three main research goals relating to ambient sound environments that this thesis work attempts to complete. These three research goals include creating aircraft probability of detection models through nominal logistic regression, applying quantile techniques and distribution-based assumptions to data collection and processing, and building an ambient sound matching function which enables any random ambient sound environment to be matched to the closest existing environment from the dataset with human-response information.

Regarding the first goal of this thesis, creating aircraft probability of detection models through nominal logistic regression, 18 different aircraft probability of detection models were created by sorting the dataset into sub-datasets based on helicopter type (2 different helicopters) and ambient environment (9 different ambient environments). The findings from this will research goal will be discussed in Section 3.1. The second goal of this thesis, applying quantile techniques and distribution-based assumptions to data collection and processing was conducted using the quantile function in Matlab as well as equations built on symmetric and normal distribution principles to analyze and compare ambient acoustic profiles. The findings from this will research goal will be discussed in Section 3.2. The last research goal that this thesis research attempts to meet has to do with building an ambient sound matching function which enables any random ambient sound environment to be matched to the closest existing environment from the dataset with human-response information. This research goal is approached by creating a matching function in Matlab based on the the Sum of Squared Errors and will be discussed in Section 3.3. A very important key to understanding the research done in this thesis is having a firm grasp on the composition of the Hoglund *et al.* dataset used in this research, which will be discussed in the subsequent paragraphs.

Hoglund *et al.* (2008), were interested in exploring how ambient environment noise affected the human probability of detection of an aircraft's acoustic emission, since relatively little experimentation had been conducted on this topic. They developed a human-based experimental study and recorded how an acoustic stimuli from two different helicopters was perceived by a human listener in various ambient environments [1]. The data used in this research comes from that experimental study. The MD-902 and the MI-8 were the two helicopters recorded in the study. These helicopters were operated out of Eglin, AFB in northwest Florida and flew during an operation conducted in 2007 called "Chicken Little". Hoglund *et al.* (2008), were interested in understanding how human listeners interpreted the acoustic stimuli of an aircraft flying overhead a position, so they recorded one-second long samples of the acoustic emission of the helicopters flying overhead discarding the takeoff and landing acoustic emissions [1].

Recording a diverse selection of ambient environments was another important part of this human-based study. Eventually nine (five-second long) ambient environment sound recordings from different locations across the United States were selected for use in the study, from urban, suburban, and rural sound environments. Three of these ambient sound environments were recorded at Eglin, AFB; the same environment that the helicopter recordings were made during the "Chicken Little" exercise. These three ambient recordings were chosen out of a larger number of recordings conducted in this location and selected based on their low, medium, and high sound levels. The recording with the lower background noise emission consisted of "no discernible environments noise", the recording with the medium background noise emission consisted of "primarily insect noise and occasional birds", and the high background noise emission consisted of "sounds of clothing rustling and some speech and other human generated sound" [1]. Furthermore, during the recording, no helicopter noise entered into the ambient environment recording, so no acoustic contamination occurred. The microphone recording setup used at Eglin, AFB can be seen in Figure 1. The three recordings are labeled as "Ambient19", "Ambient5", and "Ambient28", respectively, and are referred to as such in this thesis [1].

Another three out of the nine ambient sound recordings were obtained from an acoustics consulting firm, HMMH, located in Massachusetts. The three ambient environments they recorded included Boston Common park located in an urban setting, a road in a suburban setting in Newton, MA, and a road in a rural setting in Boxford, MA. These ambient environments were chosen to provide a wide variety of sampled ambient environments such as what an aircraft might fly over while carrying out a mission. The locations of these three ambient locations (where the sound associated with the respective environment was recorded) are shown in Figure 2. The three recordings were labeled as "Urbancorr", "Suburbancorr", and "Ruralcorr", respectively, and are referred to as such in this thesis [1].

Figure 1. Microphone Setup Used for Acoustic Recordings Eglin, AFB [1]

The last three ambient sound environments were recorded in urban settings from Dayton, OH. These three environments included an area outside of a courthouse, a street setting located at 3rd and Patterson, and a setting outside of a National City bank. The microphone setup employed was built to mimic the auditory height of a human listening for an aircraft in that respective environment. The microphone configuration for these recordings is displayed in Figure 3. The three recordings were labeled as "Courthouse", "Patterson", and "NatlCity" respectively, and are referred to as such in this thesis [1].

For the human-based auditory performance experiment, fourteen subjects were given extensive training before attempting to identify whether or not they could distinguish the helicopter from the ambient environment. These subjects varied in age from 19 to 57 years of age and qualified for the study by passing a test that deter-

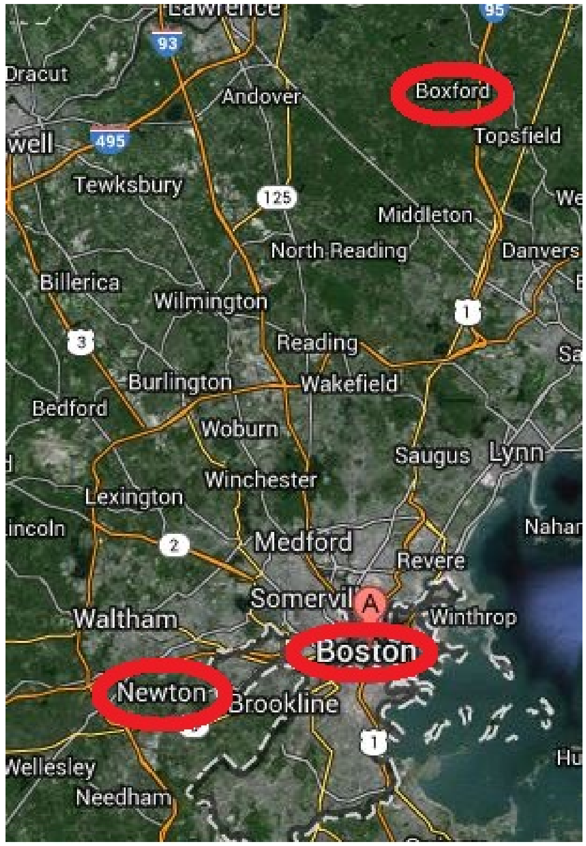

Figure 2. Locations of the Three Ambient Environments Recorded in Massachusetts [1]

mined whether or not they had "normal hearing". "Normal hearing" is defined in the study as "air conduction thresholds at 20 dB Hearing Level (HL) or better for octave frequencies between 250-8,000 Hz" [1]. The training that these subjects were exposed to before their responses were recorded as observations in the study included several days of responding to simulated practice runs of the helicopter acoustic stimuli overlaid on different acoustic signatures of various ambient environments. This allowed the subjects to get a better idea of what the various stimuli and ambient environments sounded like. The conditions for the training runs were identical to the actual runs recorded in the study [1].

In each trial, subjects were asked to listen to a minimum of 12,000 six-second long randomly selected trials (varying based on MD-902/MI-8 helicopter and the 9

Figure 3. Microphone Configuration for Dayton, OH Recordings [1]

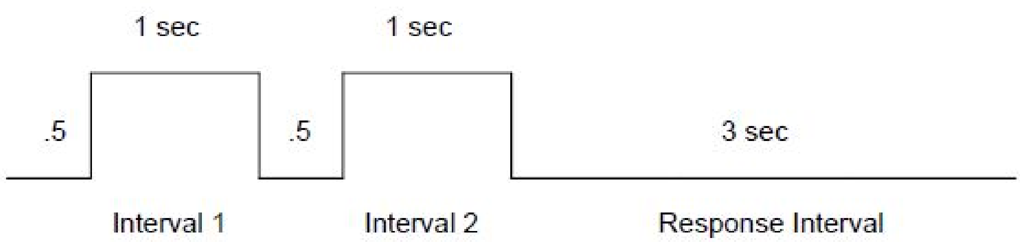

Figure 4. Sound Interval used in Experimental Trial [1]

ambient environments). Figure 4 displays the time interval over which a six-second long trial was played to the human in the experiment, [1]. Each interval consists of a half-second long warm up period, followed by a one-second interval in which the helicopter stimulus could or could not be played, followed by another half-second interval. This is then followed by another one-second interval in which the helicopter stimulus could or could not be played, and lastly, a 3 second interval in which the human can respond to what they heard as seen in Figure 4. Since the helicopter stimulus is only played in one of the second long intervals, the interval in which it is not played is filled with a one-second long "soundscape", recorded from the ambient environment during the acoustical testing done at Eglin, AFB. If the test subject correctly identified which interval the helicopter noise was emitted, they received a "1" in the response variable. If they incorrectly chose which interval the helicopter noise was emitted in during the trial, they received a "0" in the response variable. All of the human response, stimulus, and ambient environment data were then compiled into a large dataset. This dataset is used throughout this thesis research.

A human observer (with normal hearing ability) should be able to detect the aircraft acoustic signature when the sound pressure level (SPL) of the stimulus (helicopter) at a given frequency range is higher than the sound pressure level of the ambient environment. Figure 5, illustrates a situation involving the stimulus and ambient sound profiles from an observation in the dataset where the human listener would not be able to hear the helicopter stimulus. Figure 6, illustrates the stimulus and ambient sound profiles from an observation in the dataset where there is borderline stimulus audibility and the human listener would most likely not be able to hear it. Figure 7, illustrates the stimulus and ambient sound profiles from an observation in the dataset where the human listener would have strong probability of being able to hear the helicopter stimulus. Nominal logistic modeling will allow us to assign a probability of detection for an aircraft operating in various ambient environments based on current stimulus and ambient environment SPLs.

The nine different environments with corresponding file names and locations are listed in Table 1. These ambient sound profiles include thousands of discretized time-based observations. Each test measured the SPL at 31 different frequency intervals (measured in Hz) representing the human auditory range. Figure 8 illustrates the first five time ordered points from the Ambient Location 1 data set, which was the quietest ambient environment recording from the Eglin AFB recordings. The changing values

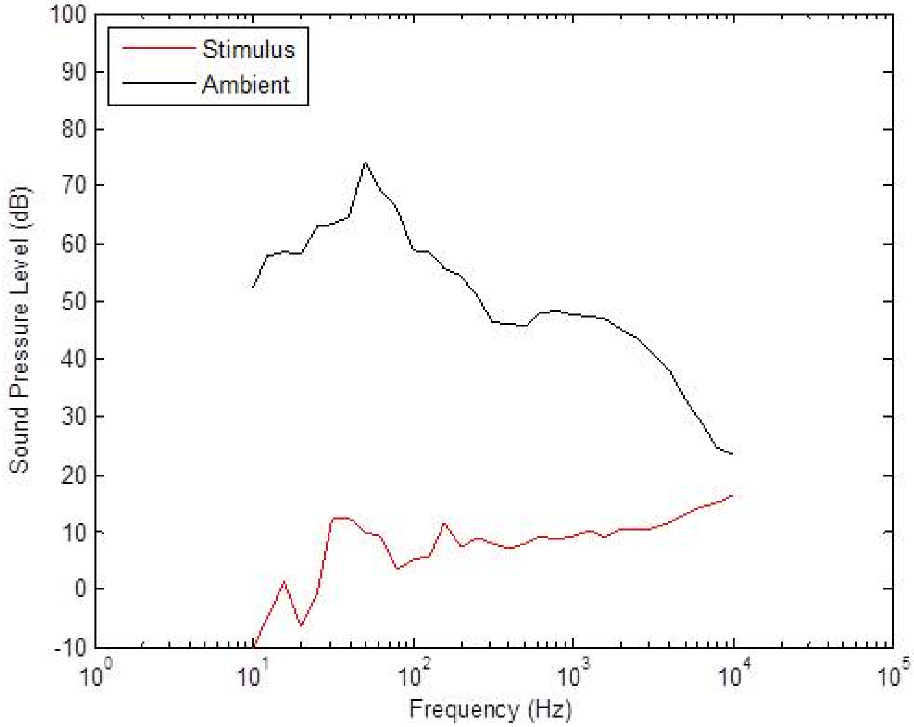

Figure 5. Inaudible Observation's Stimulus and Ambient Sound Pressure Levels

of the SPL over the frequency range in the five observations in this figure reflect the varying time-based acoustic signatures within a single ambient environment that are expected as the environmental sound profile is recorded. Figure 9 illustrates the first five time ordered points from the Ambient Location 6 data set, which reflects a rural acoustic setting recorded in Boxford, MA. Figure 10 illustrates the first five time ordered points from the Ambient Location 7 data set, which reflects an urban court house acoustic setting recorded in downtown Dayton, OH. These three figures clearly show how the acoustic sound trace of an environment changes based on the location and these changes in ambient SPL can have a large impact on aircraft probability of detection.

In the following chapter, principles of acoustics are discussed along with their application to both fixed wing and rotary wing aircraft. This discussion provides a

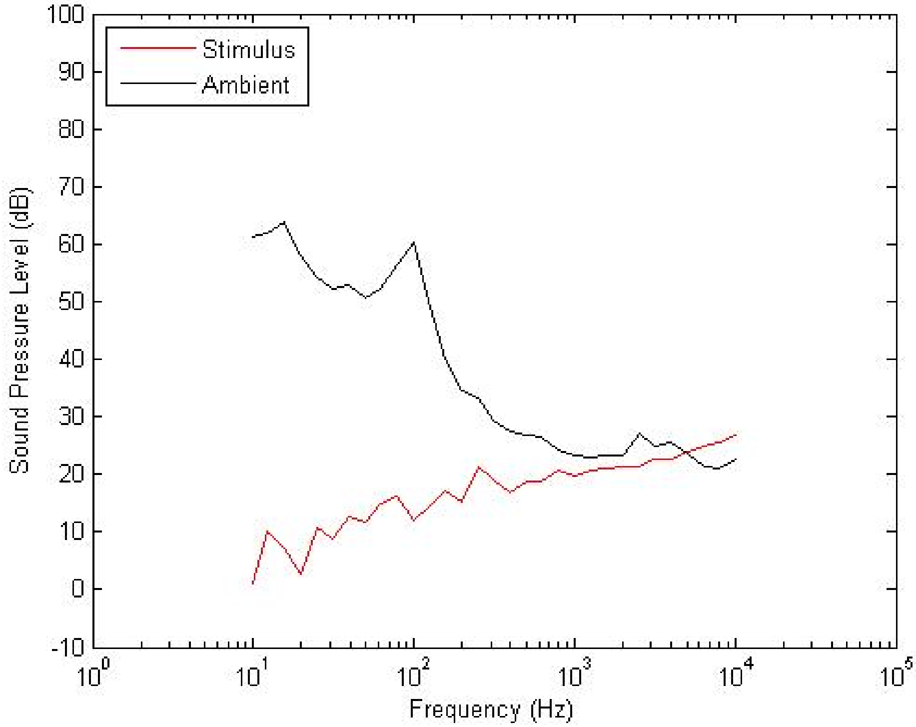

Figure 6. Barely Audible Observation's Stimulus and Ambient Sound Pressure Levels

better understanding of the current research as well as future applications for this research. In addition, the principles of logistic regression, quantiles, and the method of least squares estimation are discussed.

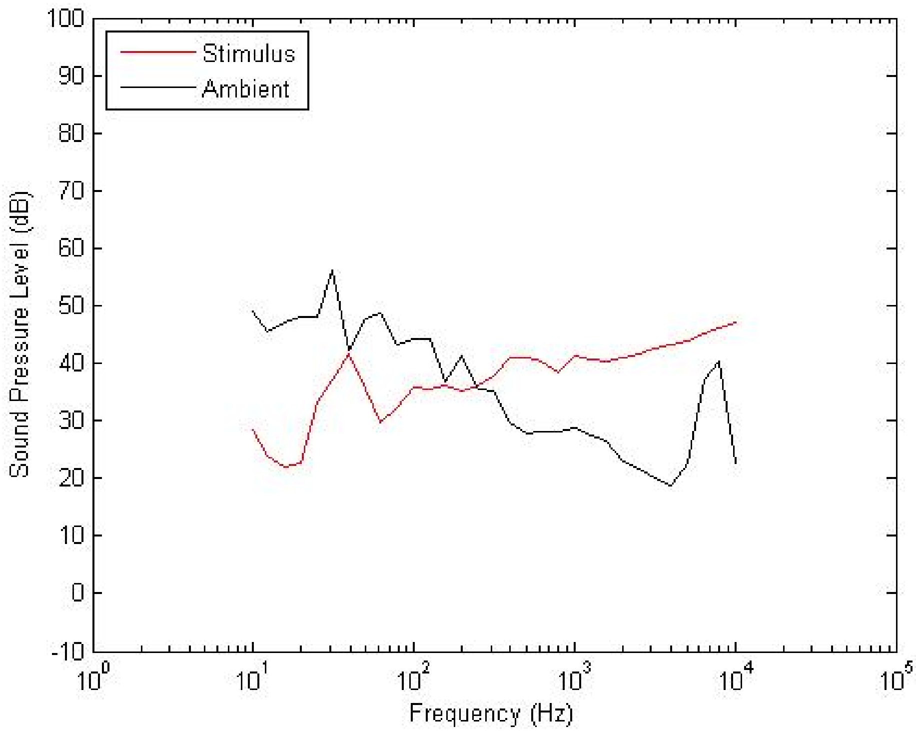

Figure 7. Audible Observation's Stimulus and Ambient Sound Pressure Levels

Table 1. Ambient Locations Described by Name and Location

Ambient Environment	Filename and Location
1	Ambient19 recorded at Eglin, AFB
2	Ambient5 recorded at Eglin, AFB
3	Ambient28 recorded at Eglin, AFB
4	Urbancorr recorded at Boston Common Park, MA
5	Suburbancorr recorded in Newton, MA
6	Ruralcorr recorded in Boxford, MA
7	Courthouse recorded in Dayton, OH
8	Patterson recorded in Dayton, OH
9	NatlCity recorded in Dayton, OH

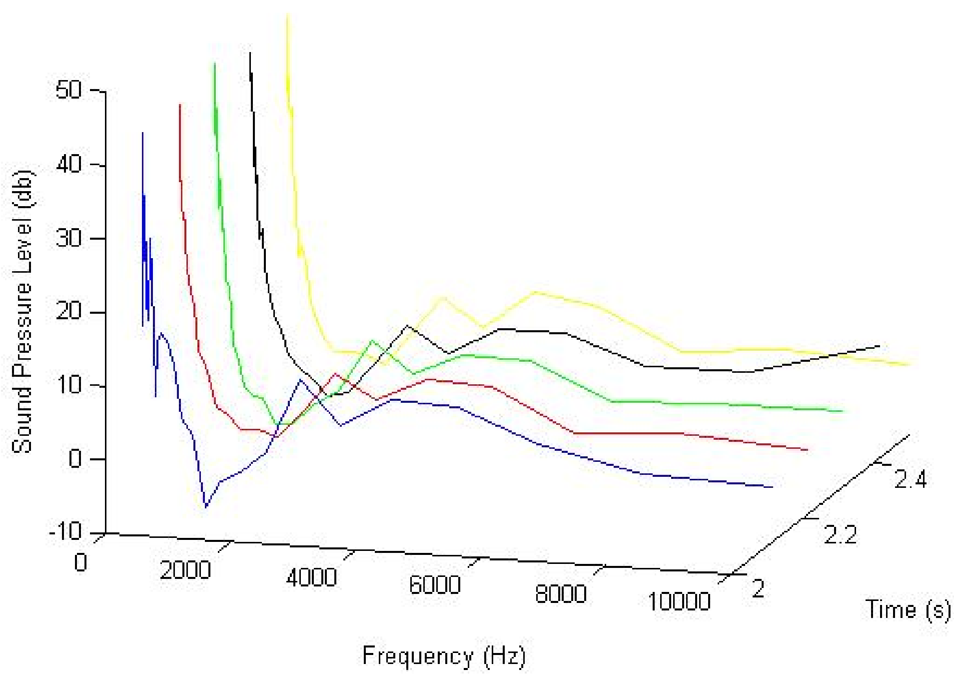

Figure 8. First Five Observations from Ambient Location 1 Sound File

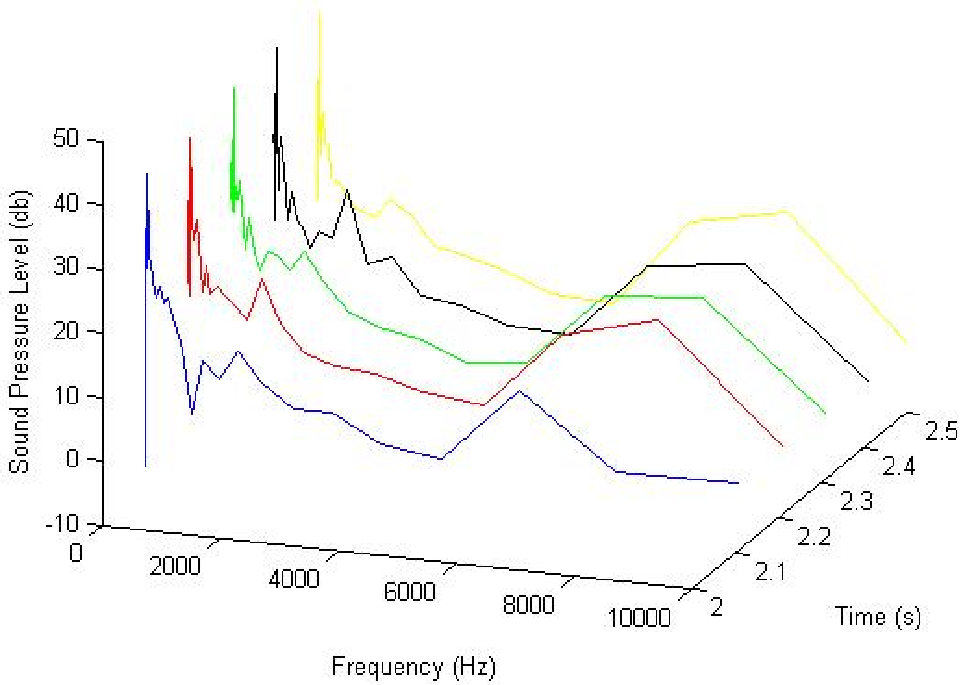

Figure 9. First Five Observations from Ambient Location 6 (Rural) Sound File

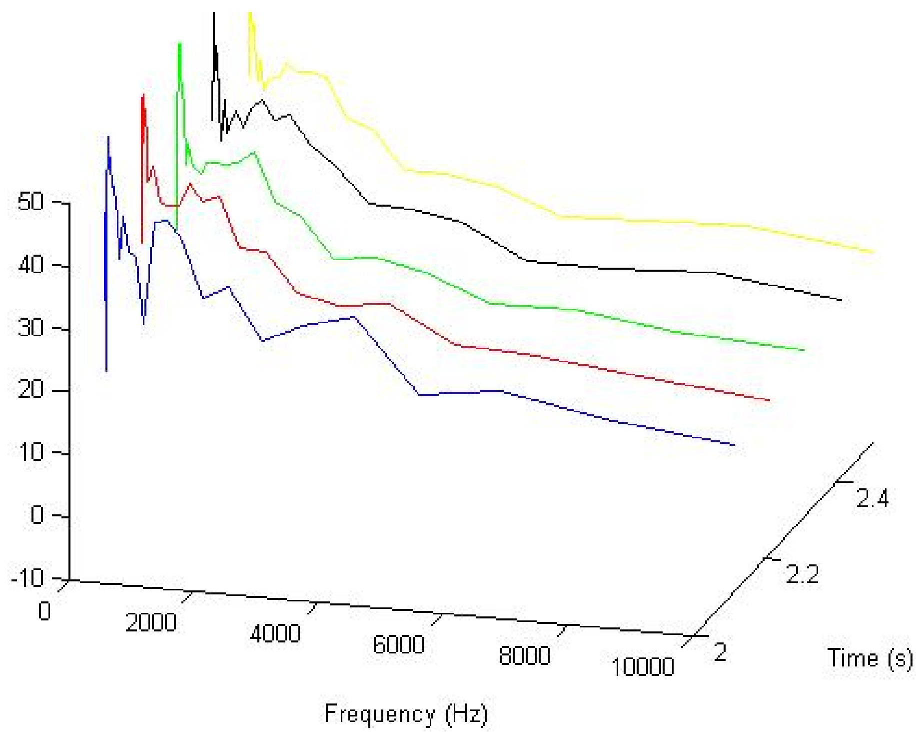

Figure 10. First Five Observations from Ambient Location 7 (Court House) Sound File

II. Principles of Acoustics and Aircraft Application

2.1 Principles of Acoustics

History of Acoustics.

Hearing, the second most utilized of the five senses after seeing, has played a major role in the human sensory process for millennia. The first recorded study of the science behind sound, also known as acoustics, occurred in Ancient China circa 2800 BCE when a minister to the Yellow Emperor Huangundi was employed to establish a tonal standard for the development of imperial music [2]. The idea of utilizing sound for military applications dates as far back as the prehistoric era when combatant groups would use sharp clanging noises in the middle of battle to scare the enemy into retreating. During the third century BCE, Alexander the Great used acoustics to create an elementary model of what is now known as the megaphone, which allowed him to communicate with troops as far as 15 kilometers away. Although most advances in acoustics were brought forth by research intended to improve musical instruments; the military application of these advances often followed quite closely and with devastating effect against an unprepared enemy. The idea of controlling acoustic emissions to provide tactical advantages is used today for many different military applications including noise reduction in submarines and aircraft among other capabilities. To understand the idea behind how these acoustic capabilities are employed, it is important to have an understanding regarding the fundamentals of acoustics [2].

The Sound Wave.

Although rarely occurring in nature, the fundamental building block of all audible sound is a single sound wave. This single sound wave is often represented pictorially as a sine wave. A sine wave representation of a single sound wave is depicted in Figure 11.

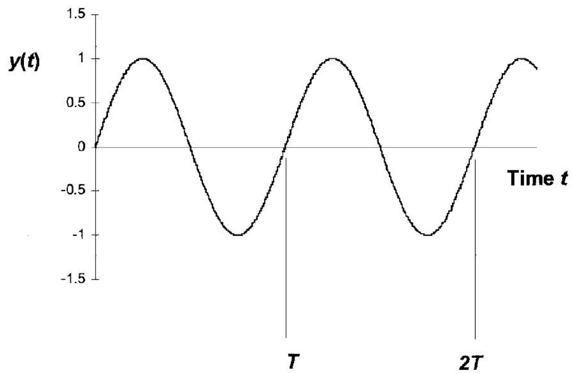

Figure 11. Acoustic Sine Wave [2]

Figure 11 illustrates how a sound wave changes over time in an oscillating fashion. The period of a sound wave, denoted in Figure 11 by interval T , is the time a sound wave takes to complete one full cycle. The number of times a sound wave oscillates over a specified period of time, or the frequency, is another important measure of sound, and is most often measured in Hertz (Hz), which equals one cycle of a sound wave per second. Equation (1) expresses the radian frequency, with w being the radian frequency of the wave, f being the normal frequency of the wave, and T being the period. The frequency of a sound wave is the determining factor regarding whether or not a sound is audible to the human ear.

$$\omega = 2\pi f = \frac{2\pi}{T} \tag{1}$$

Although sound waves are constantly present in an environment, it is not always possible for humans to hear them due to the limited range that the human auditory system can process. Typically the average person cannot hear an acoustical emission with frequencies below 20 Hz or above 20,000 Hz. Sound waves with frequencies below 20 Hz are designated as infrasonic whereas sound waves with frequencies above 20,000 Hz are designated as ultrasonic. Unfortunately, the majority of sound waves emitted from fixed-wing and rotary-wing aircraft fall within this audible range of sound, which makes it very important to understand how an enemy receiver on the ground processes sound emission from aircraft. Figure 12 expresses the accepted range of human hearing.

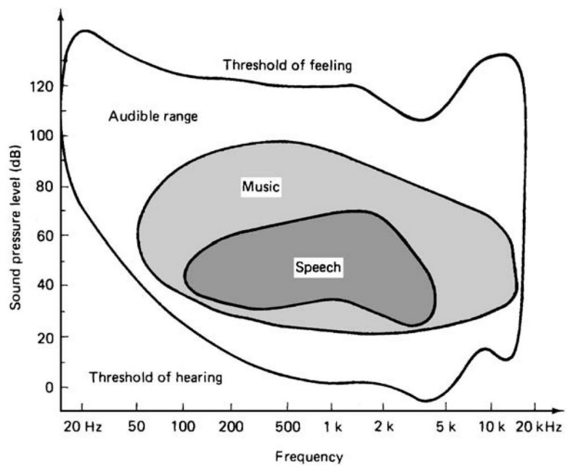

Figure 12. Threshold of Hearing for the Human Auditory System [2]

It is important to understand that sound waves are both similar and different from other wave-like entities such as light, x-rays, and gamma rays. Sound wave propagation is similar to the way that light, x-rays, and gamma rays are propagated in terms of the pattern that the waves follow. However, sound waves are also different because they require a mechanically elastic medium such as air to travel through (there is no sound in space). As a sound wave moves through a mechanically elastic medium such as air or water, the oscillating pattern that the sound wave follows causes an alternating increase and decrease of pressure. The water or air molecules that fall within the path of the sound wave vibrate against each other due to this changing pressure caused by the wave, which causes sound to be emitted.

An important measure regarding sound wave propagation is the speed of sound. The value for the speed of sound varies depending on the medium which the sound wave travels through as well as the temperature and pressure of that medium. The most common value associated with the speed of sound is 344 meters per second (m/s), which occurs in air at 20 degrees Celsius and a pressure of 101 kilopascals (kPa). Sound travels faster in solids than it does in liquids and faster in liquids than it does in gases. The formula associated with calculating the speed of sound is displayed in Equation (2). The gas constant equal to the thermodynamic ratio of specific heats is denoted by y, p is the quiescent gas pressure, and ρ is the density of the gas. The thermodynamic constant characteristic of the gas is denoted by R and the absolute temperature of the gas is expressed by T [2].

$$c = \sqrt{\frac{\gamma p}{p}} = \sqrt{\gamma R T} \tag{2}$$

The spatial distance from one point in the cycle to the corresponding point on the next cycle is called the wavelength λ. The formula for the wavelength of a sound wave, which is related to both speed of sound (c) and frequency (f) of the sound wave, is displayed in Equation (3). The wavelength measurement of a sound wave is most often recorded in meters.

$$\lambda = \frac{c}{f} \tag{3}$$

Sound is usually spread through a group of multiple sound waves as in the case of a jet engine or music coming from a set of speakers. A group of sound waves being propagated together is called a complex sound wave. Complex waves occur when multiple sound waves are generated from an object. A complex wave is a single wave that can be broken down into a group of harmonically related waves, with each increasing level of the harmonic scale being the twice the value of the previous harmonic (originating at the fundamental frequency). A harmonic is defined as a "component frequency of the signal that is an integer multiple of the fundamental frequency" [14]. This directly relates to machinery such as airplane engines, which emit sound in the form of complex waves. Noise associated with rotating machinery such as an aircraft engine oftentimes has a complex wave containing approximately 8 to 10 associated harmonics. An example of a complex sound wave is displayed in Figure 13 [2].

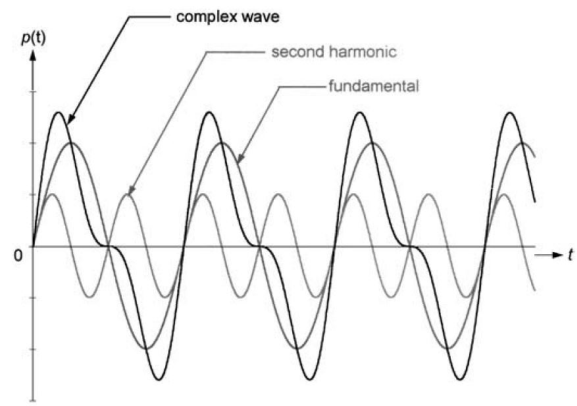

Figure 13. Complex Sound Wave [2]

The multiple sound waves making up a complex sound wave are expressed in an equation based on the principle of Fourier series and is displayed in Equation (4). In this equation A_n, is the amplitude of the nth harmonic, ϕ_n, is the phase angle of the nth harmonic, and ω is the angular frequency of the sound wave.

$$p(t) = A_1 \sin(\omega t + \phi_1) + A_2 \sin(2\omega t + \phi_2) + A_3 \sin(3\omega t + \phi_3) + ... + A_n \sin(n\omega t + \phi_n) \quad (4)$$

The Doppler Effect.

Helicopters, UAVs, and airplanes are constantly moving during flight and thus constantly emitting sound waves into the environment. An important concept in understanding how sound is emitted from a moving object is the Doppler effect. The Doppler effect expresses a dynamic property of sound waves that occurs when a source is moving through space at a constant velocity v. When an aircraft is approaching a listener on the ground at a specified velocity v, then the sound wave emitted at the beginning of the period T travels a distance of cT during a single period $T = \frac{1}{f}$. Because the aircraft is moving, the sound wave emitted at the end of the period is closer to the receiver by a distance of vT. This causes the wavelength of the sound wave to reduce according to Equation (5).

$$\lambda = cT - vT = \frac{c - v}{f} \tag{5}$$

This change in position causes the receiver to hear an increased frequency instead of the source's actual output frequency; the frequency has increased because the wavelength size has reduced due to the source moving. The resulting frequency is expressed through Equation (6) with f_d being the frequency that the receiver hears, c being the speed of sound, v being the velocity of the source, and λ being the wavelength.

$$f_d = \frac{c}{\lambda} = \frac{fc}{c - v} = \frac{f}{1 - \frac{v}{c}} \tag{6}$$

When the aircraft passes over the listener on the ground, and is moving away, the velocity is expressed as a negative number, causing a lower frequency transmitted to the receiver than the original source frequency.

Reflection and Absorption of a Sound Wave.

Sound wave behavior changes when it comes into contact with a surface. Depending on the hardness of the surface, the sound wave will either be partially absorbed and reflected (less dense surfaces) or completely reflected (very dense surfaces). Sound wave reflection causes the phenomena of the echo occurs. When a sound wave comes into contact with a hard surface, the incident ray (or sound wave first coming into contact with the surface) bounces off the surface as the reflected ray at an angle equal to the angle of incidence. This property of sound wave behavior is illustrated in Figure 14.

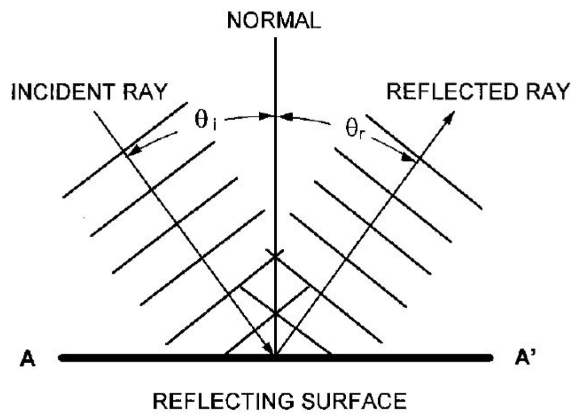

Figure 14. Sound Wave Reflection [2]

Reflection is important to aircraft acoustic modeling because if an enemy receiver on the ground is positioned next to a building, sound waves propagated from the aircraft could be completely reflected off the top of the building and miss the receiver completely. Furthermore, if the aircraft is operating in a mountainous region then the reflection of sound waves off mountains and cliff faces could have the unintended consequence of alerting the enemy to an aircraft's presence even if the enemy is nowhere near the projected angle of the sound wave from the aircraft. Conversely, if the aircraft is operating in a region where the terrain has more absorptive characteristics, the resulting sound wave attenuation could be valuable to mission planning and aircraft survivability.

Delaney and Bazley (1970), discuss the absorption of sound by different types of materials. The way that sounds react to various types of fibrous materials was recorded in an experiment to better understand how sounds are absorbed and reflected by different structures, both of which directly relate to aircraft acoustics. These types of fibrous materials include “various grades of glass-fibre and mineral-wool materials” and are “mounted in an impedance tube and the axial sound pressure distribution explored” in order to explore how the materials reacted to different frequencies of sound propagation [3]. One of their research findings is that as frequency divided by flow-resistance increased, sound dispersion also increased, which means that higher frequency sounds are easier to absorb with different absorbent materials than lower frequency sounds, as shown in Figure 15.

The amount of sound absorbed by different material depends on the surface position of the absorbing material. This idea could be applied to UAV route planning to determine that route making the fewest amounts of position changes while minimizing sound dispersion towards the ground. It could also be applied to engine design to ensure that sound dispersion from the aircraft’s engines are absorbed as much as possible. A possible problem with the research is that the normalized data for the characteristic, impedance, propagation, reflection, and absorption coefficients, “find direct application when a sufficiently large thickness of material is to be used” [3]. This is problematic when it comes to UAV design because in general UAVs and their engines are designed to be as lightweight as possible in order to maximize loiter time and flight distance. By increasing the thickness of the engine parts and the overall weight of the engine, which results in a smaller aircraft acoustic signature, the loiter time and flight distance would be adversely affected. Therefore, the findings of this research are not as applicable to UAVs, but rather constrain the UAV development.

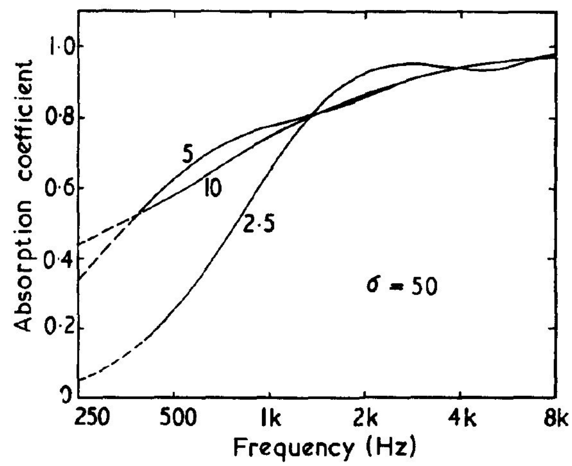

Figure 15. Change in Frequency Absorption Coefficient due to Frequency [3]

Another finding from the research involved how material density affects sound absorption. As the bulk density of material increases, the specific flow resistance of the material also increases. Therefore, when choosing a material to absorb sound propagation from airplane engines, less dense materials are preferred over more dense materials [3].

Refraction of a Sound Wave.

Sound wave refraction is a highly dynamic property of acoustics based on atmospheric conditions. Refraction occurs when the direction of the sound wave bends as it travels through different mediums due to changing in propagation velocities. One of the most important equations expressing sound wave refraction is based on Snell's law, which was developed to interpret how light is refracted as it moves through different mediums. The equation governing sound refraction is expressed in Equation (7), with θ_i being the angle of incidence, θ_r being the angle of refraction, and both c_1 and c_2 being the different speed of sound constants for the different mediums that the sound wave travels through.

$$\frac{\sin\theta_i}{c_1} = \frac{\sin\theta_r}{c_2} \tag{7}$$

Snell 's law applies to sound waves because of their similar characteristics to light waves. Refraction relates to aircraft acoustics because as an aircraft is travelling, it is emitting sound through the atmosphere towards the ground. As this sound moves throughout the atmosphere towards a receiver on the ground, movement through warmer parts of the atmosphere cause the angle of the sound wave to deviate upward from its original path and movement through cooler parts of the atmosphere cause the angle of the sound wave to deviate downward from its original path. Therefore, the assumption that the path of the sound wave transmitted from the aircraft to the ground remains constant throughout the atmosphere is only entertained in certain unique circumstances [2]. Another factor that can affect the noise propagation produced by a moving aircraft is the type of materials used to produce the noisy parts of the aircraft. The next sections cover previous research regarding the acoustics of fixed-wing and rotary-wing aircraft.

2.2 Acoustics of Fixed-Wing Aircraft

The sound profile of fixed-wing aircraft is much different than the sound profile of rotary-wing aircraft. Therefore, different acoustical signatures must be considered when attempting to model these two types of aircraft. The majority of the sound waves emitted from a fixed-wing aircraft originate from the engine and the engine propeller. A great deal of research has been conducted to determine what the acoustical signature of an airplane looks like and the factors that affect its spherical harmonic output. The application of aircraft noise reduction research interests the military. The less audible an aircraft, the less the aircraft is heard, and the more likely the aircraft will be able to carry out its mission unimpeded by the enemy.

Oleson and Patrick (1998) conducted noise reduction testing on a small airplane by placing a duct on its propeller to explore how the application of this technology could reduce the overall acoustical signature of the aircraft. This technology can also be applied to other current research topics in the field of acoustics including duct acoustics, rotor-stator interaction tones, and engine exhaust noise. The overall aircraft sound profile resulting from the combined noise from the aircraft engine and the propeller is depicted in Figure 16.

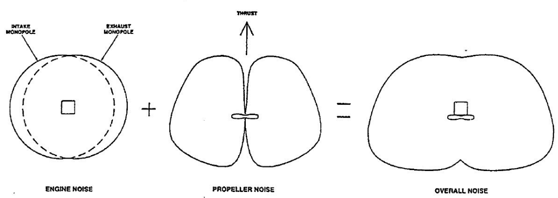

Figure 16. Aircraft Engine and Propeller Sound Profile [4]

The Oleson and Patrick experiment was conducted with "a 35 horsepower ultralight engine, a four bladed ultralight propeller, and a duct constructed of foam core covered with fiberglass," which acts as a noise muffler for the propeller. The ducted propeller system works by "reducing the noise due to elimination of tip vortices" as well as "providing a platform for implementing active noise control techniques to reduce the levels of noise emitted from the duct" [4]. Much like the research done on tactical UAVs at Georgia Tech [6], this research involved microphones placed strategically around the aircrafts flight path in order to best record the acoustic signature of the vehicle flying overhead as depicted in Figure 17.

The Oleson and Patrick research experimented with two different aircraft configurations, with and without a ducted propeller. In using the ducted propeller, the researchers found that the two primary sources of noise coming from the ultralight aircraft emanated from the engine and the propeller noise. An interesting finding from this experiment was that the majority of the noise was caused by the propeller

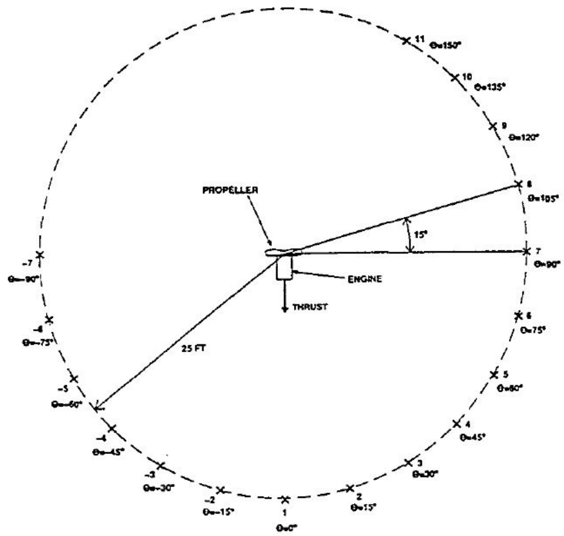

Figure 17. Microphone Placement for Sound Testing [4]

versus the engine. They also found a lack of symmetry in the propeller noise around the airplane. The results showed that the propeller noise on the intake side of the engine was higher than the propeller noise on the exhaust side of the engine, which was attributed to turbulence during the flight. This could be important to study for military aircraft to ensure aircraft acoustic models consider a possibly uneven acoustic signature. An uneven acoustic signature could cause the noise output to be dispersed differently on each side of the aircraft and would challenge most aircraft acoustic signature models, which typically assume a symmetrical and spherical sound dispersion from the aircraft.

The ducted propeller was examined to reduce aircraft noise. Surprisingly, with the ducted propeller configuration, the sound pressure level (SPL) actually increased by approximately six decibels. This increase in SPL was attributed to "an increase in levels of higher frequency tones which are attributed to rotor-stator interaction" [4]. Although this research did not go as planned, it was an important step in beginning to test various configurations of ducted propellers to reduce noise emitted by ultralight aircraft, and directly relatable to fixed-wing acoustic emissions of tactical UAVs.

This research should be considered when developing more noise efficient propellers for tactical UAVs deployed in wartime environments [4].

UAV Survivability.

As military UAV's become more expensive due to increased functionality and capabilities and their functions become more critical to mission success, the ability to increase their survivability by protecting them from enemy detection becomes a greater concern for the military. Understanding the acoustic profile of UAVs employed on the battlefield is one of the most important aspects of increasing UAV survivability and also mission effectiveness [5]. One way to better understand the acoustic signature associated with UAVs is through testing, using an array of microphones placed around the UAVs flight path acting as ground listeners. Figure 18 displays a microphone array setup used to record the acoustic profile of a UAV.

Figure 18. Microphone Array Setup [5]

The acoustic signature of a UAV generated from SPL data recorded using a microphone array can be seen in Figure 19. A unique acoustic signature for a UAV is generated based on varying speeds and altitudes that the UAV operates at during a mission. This knowledge is helpful at improving UAV survivability when it comes to flight path planning. By combining knowledge of a UAVs acoustic signature, the battlefield terrain, and the atmospheric conditions, to alter the planned flight path, UAV survivability can be significantly improved [5].

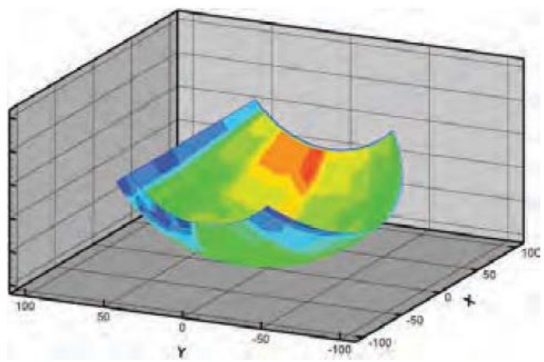

Figure 19. Sound Hemisphere of a UAV Acoustic Profile [5]

Massey and Gaeta (2010) researched the noise produced by various tactical UAVs to explore how well they may perform in various battlefield roles. From the years 2000 to 2008, the number of UAVs employed by the Department of Defense increased from approximately 50 to 6,000. This increase in the size of the UAV force prompted further Research and Development efforts to increase their battlefield effectiveness. The survivability of UAVs is a major focus, and understanding the acoustic signature of UAVs is one way to increase survivability [6].

A big problem with current UAV technology is their audibility by the ground observer before the UAV can locate their target. This is because intelligence, surveillance, and reconnaissance (ISR) UAVs "have either 2-stroke or rotary internal combustion engines with little to no noise treatment which results in high noise levels being radiated by the power plant" [6]. Another issue is the large amount of noise emitted by the UAV propeller, which is generally designed solely for performance purposes. These two sources of noise can cause the aircraft to be audible to the enemy ground forces. Research is being conducted at the Georgia Tech Research Institute (GTRI), among others, in order to reduce the amount of noise being emitted from a UAVs propeller and engine, while reducing as little power as possible [6]. Massey and Gaeta's research was performed using four microphones with booms and windsocks, placed approximately 25 feet away from the aircraft nose, tail, and two wings of the UAV flying overhead. This is depicted in Figures 20 and 21.

The UAV was flown by military personnel and operated at three power settings for the engine (idle, cruise, and max throttle). One of the main problems in this research was the high variability of sound pressure levels (SPL) during outdoor noise measurements. During the best conditions, the SPL can vary as high as eight decibels over 200 feet due to atmospheric absorption of sound, meteorological effects, and effects of local terrain. This variability must be accounted for when processing acoustic measurements. Another possible problem with the results from the experiment involves the difference between how microphones record sound and how the human ear hears sound [6].

Microphones, unlike the human ear, are built to have a flat frequency response, which means that the microphone can record the high and low frequency emissions from a UAV that a human on the ground would not be able to hear. The problem of inaccurately modeling human hearing using machine acoustical recording techniques was solved in this experiment by applying A-weighting to the data. A-weighting adjusts the sound frequencies recorded by a microphone to more accurately depict the sound frequencies that a ground observer would be able to hear. Despite these possible issues with the data, important conclusions were gained from the experiment. One of these findings was that noise reduction is affected more by altitude than distance.

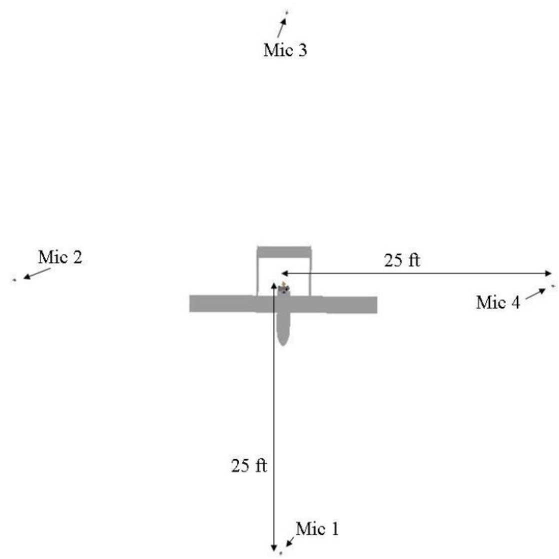

Figure 20. Microphone Placement for Sound Testing [6]

Therefore, UAVs should be flown at higher altitudes in order to avoid detection from the enemy [6].

Figure 21. Microphone Configuration with Boom and Windsock [6]

An important finding was that "for a tactical UAV the trend with altitude is consistent with other aircraft noise data gathered over 60 years ago" [6]. Clearly tactical UAVs are much louder than they could be due to how much smaller and lighter they are than aircraft produced in the 1950s. An additional interesting finding in terms of the UAV noise propagation is that the amount of noise emitted increases steadily as the UAV approaches its target and then drops off rapidly after passing over the target. This could be important tactically if UAV flight patterns were changed to remain at higher altitudes until the aircraft passes over a possible target and then quickly drop down to lower altitudes for increased surveillance and better target acquisition with a much lower probability of aural detection. Learning more about the acoustic signature of tactical UAVs and attempting to improve the acoustic design of both the engine and propeller of these aircraft can be pivotal in increasing the effectiveness of USAF tactical air missions [6].

Sound Absorbent Materials in UAV Engines.

Different types of materials used in engine and manufacturing can also reduce the overall noise of these aircraft. The type of material used to build an aircraft effects the strength of the sound waves it propagates. Iwata *et al.* (2007), experiment with a short haul UAV cargo transportation system, utilizing a three-dimensional transportation robot (3DTR), constructed with "twin turbojet engines equipped by high performance noise reduction system". A focus of this research was the creation of the noise reduction system in order to help with loud noise (approximately 110 decibels) that the turbojet engine emits. Figure 22 below depicts the design of the turbojet engine.

The two materials used in this quiet turbojet engine depicted in Figure 22 were glass fiber and polyurethane. Glass fiber was used to reduce low frequency band noise emissions and polyurethane was used to reduce high frequency band noise emissions, with results displayed in Figure 23. These results show that at lower frequencies glass fiber has a higher loss coefficient than polyurethane and at higher frequencies, this property switches for the two materials and polyurethane has a higher loss coefficient

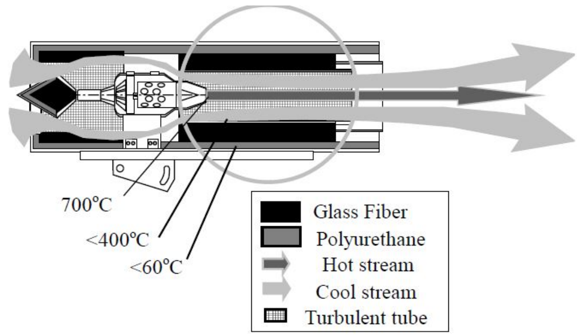

Figure 22. Turbojet Configuration [7]

than glass fiber. This is important because it indicates that a combination of both glass fiber and polyurethane are needed in an aircraft engine so that both high and low frequency acoustical emissions from the engine are minimized.

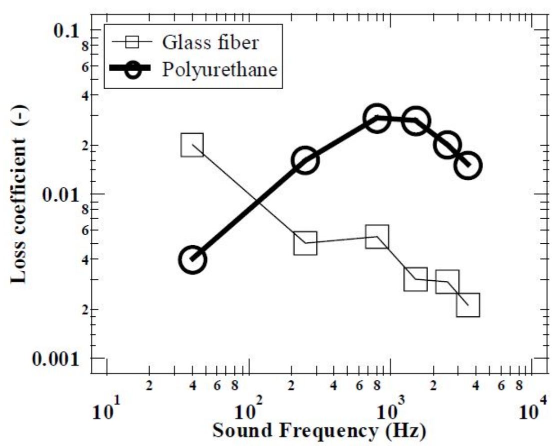

Figure 23. Glass Fiber and Polyurethane Sound Reduction [7]

A highly efficient noise reduction system was created by combining glass fiber and polyurethane in the engine. This quiet turbojet engine technology could be very useful to the U.S. military in terms of silencing UAV sound emissions from the engines and should be looked into further. Important to simulating acoustic signatures of aircraft is building a proper testing area to better understand how sound waves are propagated from the aircraft. In the next section of this chapter, jet aircraft acoustical testing and simulation are discussed [7].

Jet Aircraft Acoustic Profile Testing and Simulation.

Every aircraft has a unique acoustical signature. To obtain data needed to build an accurate simulation model of the acoustical pattern of a jet, researchers associated with NASA built a stationary hot jet acoustic rig surrounded by microphones to better understand how a jet engine emits sound. Despite much research already available involving jet engine acoustic data collection, NASA challenged the validity of this past research and their data collection techniques based on a lack of predictive capabilities of models using this data. NASA stressed the need to build a state of the art jet engine acoustic recording rig and then collect data with this rig in order to increase model validity.

Some of the driving problems which prompted the researchers to come up with the new model for a Small Hot Jet Acoustic Rig (SHJAR), were questions associated with the "acoustic analogy underpinnings of classical jet noise theory", being "unable to predict the strong directivity of jet noise", "conflicting experimental jet noise databases", and lack of data "available on turbulence in hot jets" [8]. One of the major considerations after building the SHJAR was deciding the best way collect the jet acoustic data. Processing the acoustic data once the SHJAR was running was important towards validating the model and "acoustic measurements were performed using an array of 24 microphones placed on an arc at five-degree intervals from 50 to 165 degrees relative to the jet upstream axis" as displayed in Figure 24.

The validated SHJAR model provides the ability to study the fundamental flow and related acoustics of jet noise and an outlet to conduct low cost experiments on jet noise reduction concepts with hot flow. However, there remains the need for further research in understanding the "flow-sound relationship, and the need for detailed documentation of the flow field along with sound spectra when creating a jet noise database". Understanding jet noise and noise reduction techniques also has the potential applicability for decreasing the probability of human detection of the aircraft on the battlefield [8].

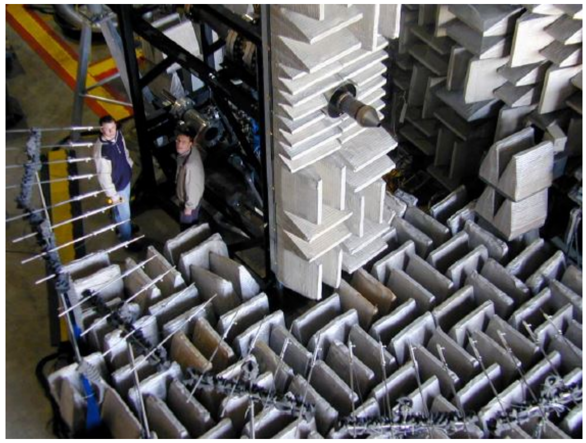

Figure 24. Microphone Array for Jet Acoustic Testing [8]

Turbulence is a main factor in predicting a jet engine acoustical signature. However, little is actually known about the details associated with "noise generation mechanisms by the complex turbulence phenomena" due to the complexity of acoustic system generated from this environment, and the computing power required for the models [15]. Two types of simulations are used to model this type of noise: Direct Numerical Simulation (DNS) and Large Eddy Simulation (LES). Each of these simulations has their own strengths and weaknesses.

One of the drawbacks of the DNS method is that due to the "wide range of length and time scales present in turbulent flows, DNS is restricted to low-Reynolds number flows and relatively simple geometries" [15]. Computing power technology is not available to properly simulate the high-Reynolds number jet flows necessary. LES is more capable of handling these types of Reynolds number jet flows because it has lower computational costs. Due to this reduction in computational costs, the first objective of the research focused on developing an LES code for turbulent noise simulation. The second objective from the LES research was to accurately predict far field noise. Uzun and Lyrintzis (2004) created and tested a Computational

Aeroacoustics (CAA) methodology for jet noise prediction by refining a 3-D Large Eddy Simulation (LES) code and incorporated integral acoustics codes into this CAA by employing "Kirchhoffs and Fowcs Williams-Hawkings (FWH) methods as well as Lighthills acoustic analogy". This LES code is used to model turbulent states of other types of aircraft including helicopters and ultralight aircraft such as UAVs [15].

The Effect of Distance on Airplane Noise.

The distance between a listener on the ground and the aircraft in the air directly affects whether the listener hears the aircraft. Regier (1947) attempted to better understand how distance affects aircraft noise by measuring sound emitted from an aircraft at various distances with a sound recorder in order to understand the acoustic signature of an airplane moving through flight. Key to understanding the acoustic signature of a moving airplane is to understand the different frequencies associated with the aircraft sound profile during flight. Lower frequencies of sound are less likely to be absorbed by the atmosphere compared to higher frequencies. Regier suggests designing an aircraft so that "the noises will occur in the higher frequency ranges in order to take advantage of the greater atmospheric absorption at high frequencies" [9]. This idea is illustrated in Figure 25. This figure indicates that lower frequency sounds travel much further distances through the atmosphere (due to less atmospheric absorption) and therefore would be heard by people much further away from the aircraft. A sound with a frequency of 10,000 eps is heard at a distance of approximately 2,000 feet from the source whereas a sound with a frequency of 100 eps is heard at a distance of over 100,000 feet from the source. Engineering an aircraft to produce lower frequency sounds would make close proximity aircraft detection much harder for ground listeners. Furthermore, if atmospheric absorption of sound is not accounted for in a sound prediction model, then the model cannot accurately predict the distance from the aircraft where an enemy ground combatant has the greatest probability of detection.

Only certain frequencies are audible to the human ear. This must be considered in aircraft design along with how sound is dissipated as it moves through the air. The two primary ways that sound is dissipated is through absorption and deflection.

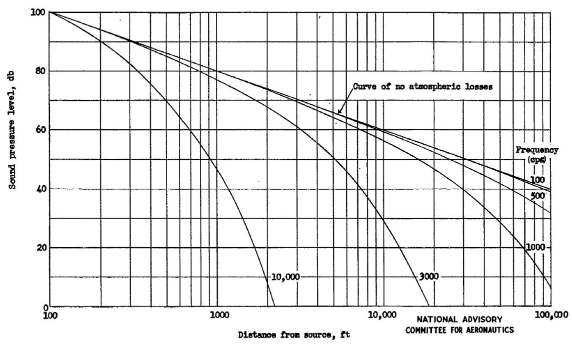

Figure 25. Effect of Frequency on Distance Sound Travelled [9]

The humidity of the air that the sound wave travels through impacts how sound is absorbed as it travels through the air. This is illustrated in Figure 26, which indicates how as relative humidity in the atmosphere increases, absorption of radiated sound in the atmosphere decreases. It also indicates that lower frequency sounds are absorbed a lot less than higher frequency sounds.

As sound levels decrease due to absorption, the sound energy is converted to heat energy. Sound absorption can be caused by conduction, water vapor, and terrain. When sound is deflected, the sound waves are broken up by scattering, partial reflections, and refraction. Regier collected sound measurements of an aircraft flying directly over a collection microphone. He used these acoustic observations taken at various aircraft altitudes to determine the effect of distance on airplane noise levels at the receiver. The range of these altitudes varied from 300 to 5,000 feet. His three main conclusions were "the range from 500 cycles to 1,000 cycles per second are found to be most easily heard even at distances of several miles", "sound data obtained with a light trainer airplane flying at various altitudes up to 5,000 feet showed good agreement with the inverse square law" which means that "for frequencies (70 to 300 cps) at which this airplane radiates the maximum noise, the atmospheric absorption is negligible", and that for attenuation losses, "of the real losses, the terrain loss is usually the greatest" and "of the atmospheric losses, the losses due to water vapor and turbulence are the most important" [9].

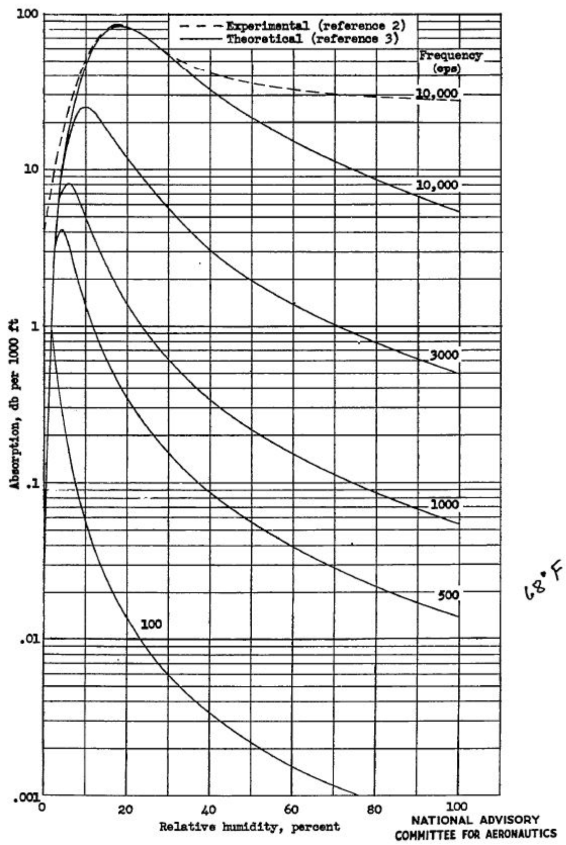

Figure 26. Effect of Humidity on Sound Absorption [9]

The acoustic signature of an aircraft at different altitudes, along with the various attenuating surfaces the noise may contact, should be considered when developing aircraft design and route planning during tactical missions where the aircraft needs to remain undetected aurally [9].

2.3 Acoustics of Rotary-Wing Aircraft

Helicopter and Rotary-Wing UAV Noise Generation.

The sound profile of rotary-wing aircraft such as helicopters and certain UAVs, differ from the sound profile of a fixed-wing aircraft. Helicopters typically sound much louder to an observer on the ground compared to fixed-wing aircraft. Helicopters also operate at a much lower altitude when carrying out tactical missions. Operational success goals make it imperative to properly understand a helicopter's sound profile. Research has focused on reducing the overall noise profile of military rotary-wing aircraft. The U.S. military conducts many of its operations at night and reducing the noise profile of tactical helicopters, like the Blackhawk, has obvious advantages since detection by visual means is already reduced.

Hoglund *et al.* (2008), discuss different research findings regarding the acoustic properties of helicopters. One finding indicates that there are two main physical parts of the helicopter with three corresponding types of noise emanated from a helicopter that account for the majority of its acoustical emission during flight. The two physical parts of the helicopter that account for the majority of noise are the rotors and the engines. The three types of noise associated with the helicopter's flight that account for the majority of the noise are the rotational noise, aerodynamic noise, and the blade slap noise [1]. Another finding indicates that low frequency sound radiated from a helicopter is heard by listeners on the ground before the high frequency sound, but are associated with less certainty regarding whether or not the human listener actually heard the aircraft. While the ground listener hears the high frequency sound later they are more certain that they heard the helicopter. This follows conventional acoustic principles, which indicate that lower frequency sound travels much longer distances than high frequency sound [16]. Therefore, a listener on the ground should be able to hear the lower frequency noise much sooner than the high frequency noise emanated from a helicopter [1].

A helicopter's acoustic emission is also affected by ground vegetation. Areas with high amounts of vegetation (e.g., jungles and forested areas) significantly affect the acoustical emission of helicopters. Surprisingly, the probability of detection in these types of environments has a positive correlation with increasing vegetation density. Finally, the probability of detecting lower frequency noise increases during nighttime and probability of detecting higher frequency noise increases during daytime. Helicopters operating during midday have the highest probability of detection by ground listeners and helicopters operating during the evening have the lowest probability of detection by ground listeners. This knowledge is very important towards understanding the acoustic properties of rotary-wing aircraft as well as the flight-planning of military operations [1].

Helicopter acoustic research originally only focused on reducing vibration among rotorcraft, but it was quickly determined that noise reduction went hand-in-hand with vibration reduction and could be extremely valuable to both civilian and military applications. The loud sound that is heard when a helicopter passes overhead is produced by blade-vortex interaction (BVI) noise, which originates in the rotors and this BVI is what the active-twist rotor technology attempts to reduce. This is caused by the constantly changing the aerodynamic environment that the blades of the rotary-wing aircraft have to constantly cut through as displayed in Figure 28.

Booth and Wilbur (2002) present an in depth analysis of the use of an active-twist rotor to reduce vibration and noise in helicopters and explore use of rotorcraft UAVs. Currently, helicopters and rotorcraft have blades that can shift the angle at which they are positioned in relation to the ground. The active-twist rotor technology is revolutionary because it allows the blade to change its angle at which it is positioned in relation to the ground at the point closest to the rotorcraft as well as at the point of the blade furthest away from the rotorcraft. This is illustrated in Figure 27. If this technology is adopted by the military and employed on military helicopters, this would lead to a significantly reduced sound profile of this type of aircraft.

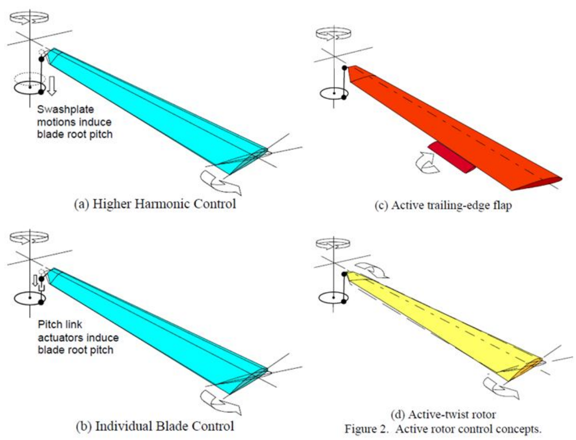

Figure 27. Rotorcraft Blade Progression [10]

The active-twist rotor research was conducted in the Langley Transonic Dynamics Tunnel (LTDT) using the Aeroelastic Rotor Experimental System (ARES) helicopter test bed. The rotor blades on the ARES helicopter were linked to active fiber composite (AFC) actuators, which twisted the rotor blades depending on the flight environment. Three microphones were mounted upstream and downstream of the ARES helicopter to record the noise coming from the rotor blades. The "acoustic data system was triggered by the ATR control system for each data point" and the "microphone signals were each sampled at 1,024 samples per rotor revolution" which resulted in 11,700 samples per second and a total data collection time of approximately five seconds [10].

An interesting idea for further research involves experimenting with an ultralight UAV flown with this rotor blade technology and comparing its sound performance with the actual helicopter. The weight and power associated with flying a helicopter could produce a much different noise signature than flying a tiny UAV only equipped with a camera. However, the noise given off by a small UAV might be so negligible

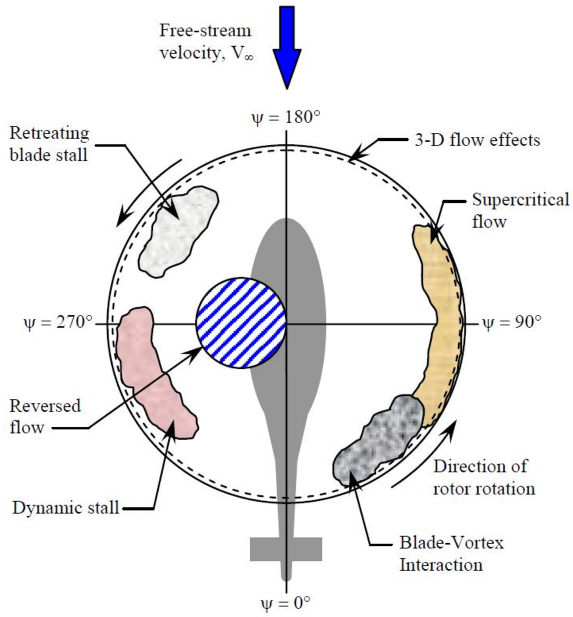

Figure 28. Rotary-Wing Aircraft Aerodynamic Environment [8]

that it would not matter whether or not it had the active-twist rotor technology. The results of this research show that the active-twist rotor system decreases the BVI of the helicopter by a maximum of 5.6 decibels. While 5.6 decibels does not seem a large improvement, it is a good sign that this technology may produce better noise reductiong results in the future [10].

UAV Noise Generation.

While Active-Twist rotor would benefit helicopters, it can also help reduce vibration and noise in UAVs. Some of the main problems associated with using rotary-wing aircraft for flight due to the "edgewise" flight of the rotor system is, "high vibratory loads, noise generation, poor performance, instabilities, difficulty maintaining rotor blade track, and limitations on load capacity and forward flight speed" [17]. These conditions are aggravated as a rotary-wing aircraft moves forward through the air and cause periodic vibratory loads to be produced. These loads cause the "wop-wop" sound emanating from the propellers of rotary-wing aircraft. One of the first ways that this acoustic problem was addressed involved modifying pitch of the rotor blades to increase the harmonic frequencies above the rotor rotational frequency. This method significantly reduced vibration and noise by changing the frequency emitted at the root of the propeller blades [17].

Although advances in rotor-blade technology have been made since 1970, the new active-twist rotor has not been tested on manned flight systems yet due to concerns with the complexity, development costs, and most importantly inherent risks associated with testing a new system with live pilots inside. However, with the new surge in UAV rotor-wing aircraft technology, the active-twist rotor control can be tested using UAVs as a blueprint for future manned flights. Active-twist rotors differ from rotors currently being used by utilizing "piezoelectric fiber composite actuators that are embedded directly within the composite blade structure" and "these actuators, when excited using electrical voltage, produce strain-induced twisting motions of the blade" [17]. By straining the twisting motions of the blade depending on the different flight environments encountered throughout a sortie, the vibration and noise of the rotors can be reduced greatly.

A possible problem with the active-twist rotor technology is that low frequency noise actually increased for all actuated flight conditions over the current unactuated technology. This could be problematic if enemy forces have the capability to use sensors to detect low frequency sounds emanating from helicopters and UAVs. Despite this problem, the actuated rotor blades were successful in reducing the sound pressure level (SPL) for all actuated conditions over the unactuated flight. This technology looks very promising towards using for military applications and should be tested further to examine the effect of low frequency emissions of the rotor-blades [17].

III. Methodology, Results, and Analysis

3.1 Logistic Regression Modeling

Nominal Logistic Regression Background.

Model building to predict the probability of detection of an aircraft's acoustic signature during flight can be an extremely valuable tool. Using such a model can increase aircraft survivability as well as mission effectiveness. If ground combatants cannot hear an aircraft in close proximity to them, they will not shoot at it or attempt to hide from it. This in turn increases UAV survivability and mission effectiveness. UAVs carry out various intelligence-based and offensive missions. UAV utility is frequently deterred by the noise radiated by their engine and propeller, which alerts the battlefield combatants the UAVs are in the area at a much further distance than their onboard cameras, sensors, and weaponry are effective [6]. Therefore, knowing where an aircraft's noise has the highest probability of being dispersed during operational use based on the predictive output of some predictive model, can help mission planning choose the most acoustically effective flight path for an aircraft mission. Until aircraft are developed with acoustic stealth, their acoustic noise profile must be accomodated.

The long-term solution to this problem would be to engineer the aircraft's engine and propeller in a way that decreases the amount of radiated sound. Until such sound radiance advances are made, one of the best tools to reduce the ability for a ground combatant to hear an aircraft is through predictive model building. This research examines the ambient environment's impact on an aircraft's probability of detection. Therefore, nominal logistic regression models will be built to detect if, "relative to the sensitivity (threshold) of human hearing in each critical band, there is sufficient signal relative to the background ambient noise, to trigger detection" [1].

This thesis uses 18 datasets to build 18 predictive models. These 18 datasets are derived from the Hoglund *et al.* human-based study of ambient noise. The original dataset contained all observations from the Hoglund *et al.* (2008) human-based study exploring an ambient environment's impact on aircraft probability of detection. This consisted of two acoustic stimuli from two different helicopters as well as nine different ambient environments in which these stimuli were played over. This original dataset was seperated into 18 smaller datasets based on the combination of helicopter stimulus and a unique ambient environment.

The columns in each of these 18 datasets consisted of a response variable made up of 0's and 1's, 31 columns indicating the sound pressure level (SPL) of the helicopter stimulus at 31 different frequencies on the chosen frequency spectrum (10 to 10,000 Hz), and 31 columns indicating the SPL of the ambient environment (that the stimulus was overlaid on) at the same 31 evenly spaced frequencies along the chosen frequency spectrum. These 18 datasets were further reduced by subtracting the 31 columns of the ambient environment SPL from the 31 columns of the helicopter stimulus SPL and using 31 new columns indicating the difference between these two measurements as the 31 regressor variables for model building. This resulted in 18 different datasets with 32 columns each and varying row lengths based on the number of human performance observations taken with the unique helicopter stimulus and ambient environment.

The response variable is binary data. A value of "1" indicates that the observer correctly identified the interval in which the stimulus SPL was played over the ambient environment SPL. The response variable containing a value of "0" indicates that the observer incorrectly identified hearing the stimulus in the interval in which the stimulus SPL was not played over the ambient environment SPL. We formulate a predictive model for the human-based experiment data set.

A nominal logistic model captures the probability a human observer will correctly identify whether or not the helicopter is detectable from the ambient noise. The nominal logistic regression model function, with r_1 and r_2 equaling the two levels of the response, is displayed in Equation (8) [18].

$$\log \frac{P(Y = r_1)}{P(Y = r_2)} = Xb \tag{8}$$

A nominal logistic regression model was created for each of the eighteen unique environments (two helicopters studied at nine different ambient environments) and the associated coefficients for these 18 models can be seen in 2 and 3. The regression coefficients that are bold and italicized are the significant regressors in each model.

The model outputs indicate that there are many significant regressors within the model. The significant regressors indicate which areas along the frequency range are of most statistical value in relation to aircraft detection by a ground observer. By focusing on where along the frequency range an aircraft is most vulnerable to ground detection in each environment, those in charge of designing the aircraft will have a better idea of what types of acoustic emissions to try to avoid if the aircraft will be operating in primarily one type of setting. Across all 18 models the frequency range which was most often significant was F2, which was significant in 12 out of 18 models. Following F2 were F3 and F22 which were both significant in 11 out of 18 models. Following these regressors, F1, F31, and F21 were significant in 9 out of 18, 9 out of 18, and 8 out of 18 models respectively. F6, F27, and F25 were significant in the least amount of models (2 out of 18, 3 out of 18, and 3 out of 18 models respectively). This knowledge regarding the total number of significant regressors at a frequency range across all models is useful because it indicates most significant frequencies in terms of aircraft probability of detection for the full model.

Table 2. Model Coefficients for Ambient Environments 1-9 Helicopter 1

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
Int	-0.286	***-1.052***	***-1.484***	-0.729	***-1.34***	-0.874	-0.453	***-0.644***	-0.151
F1	-0.005	0.003	0.002	0.003	0.005	0.001	***-0.006***	***-0.010***	***0.008***
F2	***0.016***	0.003	0.002	0.004	-0.004	0.005	***0.007***	***0.013***	***-0.012***
F3	0.004	0.002	***0.013***	***0.011***	***0.010***	***0.009***	***0.015***	***-0.011***	-0.001
F4	0.001	0.001	0.000	-0.005	0.005	0.005	-0.003	0.001	0.002
F5	0.008	0.004	0.003	***0.007***	***-0.008***	0.001	***0.010***	0.007	0.001
F6	-0.001	***0.014***	-0.010	-0.007	-0.003	0.003	0.004	0.007	0.000
F7	***-0.015***	-0.008	-0.002	-0.002	0.001	***0.012***	***-0.015***	***0.008***	0.000
F8	-0.001	-0.004	-0.011	-0.002	-0.008	-0.006	***-0.017***	***0.009***	-0.001
F9	-0.005	-0.008	-0.007	0.001	-0.007	-0.003	***0.015***	***-0.025***	-0.001
F10	0.003	-0.005	0.001	0.004	0.002	0.011	***0.010***	***-0.030***	0.005
F11	-0.003	0.006	-0.008	-0.002	0.007	-0.013	***0.023***	***0.020***	0.003
F12	0.012	-0.004	-0.002	-0.012	0.011	***0.025***	***-0.043***	-0.010	***0.013***
F13	-0.003	***-0.018***	***0.024***	***0.018***	-0.008	-0.005	0.009	0.005	-0.010
F14	***-0.033***	0.004	***-0.029***	0.005	-0.013	-0.007	-0.010	0.005	***0.023***
F15	-0.007	0.002	-0.017	***-0.027***	-0.013	***-0.013***	-0.006	0.005	-0.002
F16	0.024	0.012	***0.025***	-0.003	***0.025***	***0.019***	***0.020***	0.010	0.004
F17	-0.021	0.014	-0.022	-0.009	0.020	-0.002	-0.012	***-0.024***	***-0.022***
F18	0.018	-0.008	-0.017	0.008	***-0.051***	-0.015	***-0.041***	0.014	0.016
F19	***0.072***	0.016	***0.046***	-0.001	-0.017	0.013	***0.041***	***-0.050***	0.007
F20	***-0.062***	-0.023	0.018	-0.006	0.021	0.003	-0.023	0.016	0.004
F21	***-0.045***	-0.025	***-0.045***	-0.014	-0.025	***-0.072***	***0.063***	***0.029***	***-0.042***
F22	***0.044***	***-0.051***	-0.011	***-0.032***	-0.003	***-0.039***	***-0.053***	-0.005	***0.034***
F23	-0.051	-0.025	***0.059***	0.012	0.004	***0.031***	***-0.070***	-0.007	***-0.052***
F24	0.022	***0.079***	***-0.043***	0.009	-0.001	-0.024	***0.060***	-0.009	0.007
F25	0.000	-0.005	-0.032	0.010	0.038	***0.054***	-0.023	0.005	-0.017
F26	-0.018	-0.011	0.014	0.026	***-0.055***	-0.018	***0.070***	-0.017	***0.045***
F27	-0.002	-0.028	-0.008	0.023	0.043	0.025	-0.036	***0.052***	***-0.038***
F28	-0.042	-0.014	***-0.062***	***-0.047***	***-0.092***	***-0.069***	-0.015	-0.008	***0.035***
F29	-0.019	0.011	***0.048***	-0.009	***0.162***	-0.034	0.008	***0.044***	0.029
F30	-0.007	***0.037***	0.037	0.020	-0.087	0.014	0.011	0.003	***-0.048***
F31	0.029	***-0.051***	***-0.053***	-0.018	***-0.050***	-0.002	-0.005	***-0.049***	-0.006

Table 3. Model Coefficients for Ambient Environments 1-9 Helicopter 2

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
Int	0.617	***1.025***	0.770	-0.144	0.308	***1.560***	***-1.419***	***-1.042***	***-0.938***
F1	***0.013***	0.008	***0.019***	***0.011***	***0.014***	0.008	0.003	***-0.014***	***0.0130***
F2	***0.015***	***0.016***	***0.014***	***0.012***	***0.009***	***0.017***	0.004	***0.010***	***-0.009***
F3	0.011	***0.022***	0.011	***0.012***	***0.024***	***0.027***	***0.010***	0.000	0.001
F4	***0.022***	***0.021***	***0.014***	***-0.002***	0.008	***0.021***	0.005	0.006	***0.011***
F5	-0.008	-0.007	-0.004	0.000	0.001	0.002	0.004	***0.0123***	0.004
F6	0.005	0.012	0.008	0.008	***0.020***	0.007	0.006	0.003	-0.008
F7	***-0.020***	-0.001	-0.002	0.002	0.000	0.011	-0.007	0.000	0.000
F8	***0.017***	0.008	***0.0179***	-0.001	0.001	-0.002	***-0.021***	0.011	-0.004
F9	-0.010	***-0.020***	-0.010	-0.011	-0.001	-0.003	***0.018***	***-0.021***	0.004
F10	-0.004	***-0.021***	-0.007	0.009	***-0.023***	0.006	-0.002	***-0.027***	-0.002
F11	0.005	***0.018***	0.002	0.004	-0.001	***-0.023***	***0.012***	***0.020***	-0.002
F12	-0.015	-0.008	-0.008	-0.009	0.009	0.011	***-0.025***	***-0.009***	***0.024***
F13	-0.015	-0.001	-0.010	0.014	***-0.023***	0.001	0.003	-0.006	***-0.024***
F14	***0.040***	-0.002	-0.008	***0.018***	***0.026***	0.008	-0.008	0.000	-0.001
F15	-0.023	-0.015	***-0.035***	***-0.021***	-0.022	-0.006	-0.003	0.003	-0.012
F16	-0.010	***0.031***	0.019	-0.001	***0.037***	***0.023***	0.005	0.015	0.013
F17	0.027	-0.004	***-0.029***	-0.017	-0.008	***-0.026***	***0.027***	-0.013	-0.014
F18	-0.015	0.011	0.024	0.020	***-0.037***	-0.013	***-0.048***	0.011	0.017
F19	0.026	-0.010	-0.015	-0.026	-0.017	0.005	0.018	***-0.039***	0.003
F20	***-0.055***	-0.041	-0.001	***-0.053***	0.002	-0.007	-0.007	***0.006***	0.013
F21	-0.010	0.013	0.020	***0.039***	0.027	0.014	-0.003	0.036	***-0.047***
F22	***-0.051***	***-0.049***	-0.016	***-0.037***	***-0.049***	-0.018	***-0.036***	-0.029	0.030
F23	0.011	***-0.062***	0.015	0.025	-0.012	-0.005	***-0.060***	-0.009	***-0.053***
F24	-0.027	0.049	-0.023	***-0.073***	0.001	***-0.062***	0.038	0.012	***0.056***
F25	***0.065***	-0.013	-0.011	0.046	0.021	0.038	***0.050***	-0.014	-0.081
F26	-0.012	0.008	0.004	0.022	-0.035	-0.016	***0.062***	-0.019	0.050
F27	-0.002	-0.021	0.012	-0.010	0.000	0.008	***-0.072***	0.034	-0.018
F28	-0.023	-0.038	-0.030	***-0.038***	-0.056	0.024	-0.021	0.000	0.012
F29	-0.006	-0.017	-0.039	***0.058***	***0.210***	-0.053	-0.002	0.030	***0.055***
F30	-0.050	***0.057***	***0.080***	-0.014	-0.043	***0.029***	0.009	0.006	***-0.065***
F31	***0.052***	-0.021	***-0.078***	-0.035	***-0.165***	***-0.110***	0.014	***-0.031***	0.004

These models are important because they provide predictive models to provide probability of detection values for an aircraft flying in any of these ambient environments in future. By knowing what the ambient environment SPL and the stimulus SPL are at the current time, one can predict the probability that the aircraft will be detected in that environment. This is useful because it will increase aircraft survivability as well as mission effectiveness. These models are also valuable because they can be applied to other ambient environments around the world that have similar geographic characteristics (based on the assumption that similar environments produce the same acoustic signatures), since such care was taken to record a diverse collection of ambient environments (urban, suburban, and rural). Further research should go into exploring whether or not a reduction of the number of regressors in the model would increase model validity as well as a thorough analysis to determine whether or not model assumptions have been violated. In the next chapter the method of using quantile-based assumptions to increase computational efficiency as well as the underlying distribution of the data is discussed.

3.2 Quantiles

Knowledge of the acoustic signature of an aircraft, battlefield terrain, and the atmospheric conditions which an aircraft is operating in is used to improve aircraft survivability through flight path planning. By altering an aircraft's flight path based on these factors, the aircraft noise emitted to ground listeners during flight can be minimized. The altering of an aircraft's flight path can be implemented by mission planners before the flight has occurred or through "real time" updates while the aircraft is in flight and performing its mission. The latter option has a much greater impact on increasing aircraft survivability than the pre-planned flight path because it has dynamic properties that constantly alter and update the aircraft's flight path through a computer program based on changing atmospheric conditions and ground listener environments. However, the latter option is also more computationally expensive because the computer program has to constantly make "real time" route changes through a computer program based on multiple atmospheric and ground listener variables [5]. One of the ways that this research addresses the problem of computationally expensive probability of detection modeling is by exploring the underlying distribution of the ambient environment data to find appropriate distribution-based assumptions that would help to reduce computational demands. Computationally expensive methods of sorting used in the quantile algorithm found in Matlab can be replaced by more computationally efficient algorithms based on normal and symmetric distribution-based assumptions if the data proves to resemble these distributions. Before these topics can be discussed further, quantile background information will be discussed so the reader has a good understanding of its application to aircraft acoustic radiation.

Histogram outputs of the SPL regressor data from the 31 frequency ranges of the 18 different probability of detection models from the logistic regression section of this chapter were created using JMP software to examine the underlying distribution of the data. Understanding the underlying distribution of an ambient environment data set can prove very useful if the data follows a normal or symmetric distribution. If this is the case, only the SPL mean and standard deviation of an ambient environment are needed to properly model an ambient environment in an aircraft probability of detection model. Furthermore, subject matter experts can aid the data collection process of model building by acquiring the SPL mean and standard deviation of an environment of interest before a model is built instead of model builders having to sit out in the field for days at a time recording thousands of ambient environment sound trace observations. Understanding the underlying distribution of the data can also lead to monetary savings during the data collection phase of model building. This knowledge can aid in determining the appropriate number of observations needed to maximize model validity, while minimizing experimental costs.

Calculating Quantiles.

Standard Quantile Algorithm.

Three different measurements are taken when a sound trace recording is made of an ambient environment. These measurements include the frequency range (10 through 10,000 Hz) covering the SPLs, the SPL of the ambient sound occurring naturally in the environment, and the time at which the SPLs are measured. The SPLs associated with a sound trace are unique to the environment in which they are recorded because each environment has different acoustical factors affecting the ambient sound. Previously recorded ambient SPLs from the Hoglund *et al.* (2008) data associated with the nine different ambient environments are used in the quantile section for both computational efficiency and data distribution analysis.

The main utility of quantile application to these nine ambient sound environments recorded during the Hoglund research is its application to the time dimension reduction. Without dimension reduction through quantile application, frequency, SPL, and time must be considered in model building using this data, but with quantile application the time aspect of the data can be removed leaving only the frequency and SPL data to include in model building and a much more meaningful acoust profile graphic displaying the acoustic profile of an ambient environment. At each of these nine basis ambient sound recordings, the 3,019 sound pressure level observations (measured over time) were analyzed at each of 31 frequencies evenly spaced from 10 through 10,000 Hz using quantiles to remove the time-dependency aspect of the data. An example of the pre-processed data, including the first five observations of one of the nine ambient sound profiles can be seen in Figure 29.

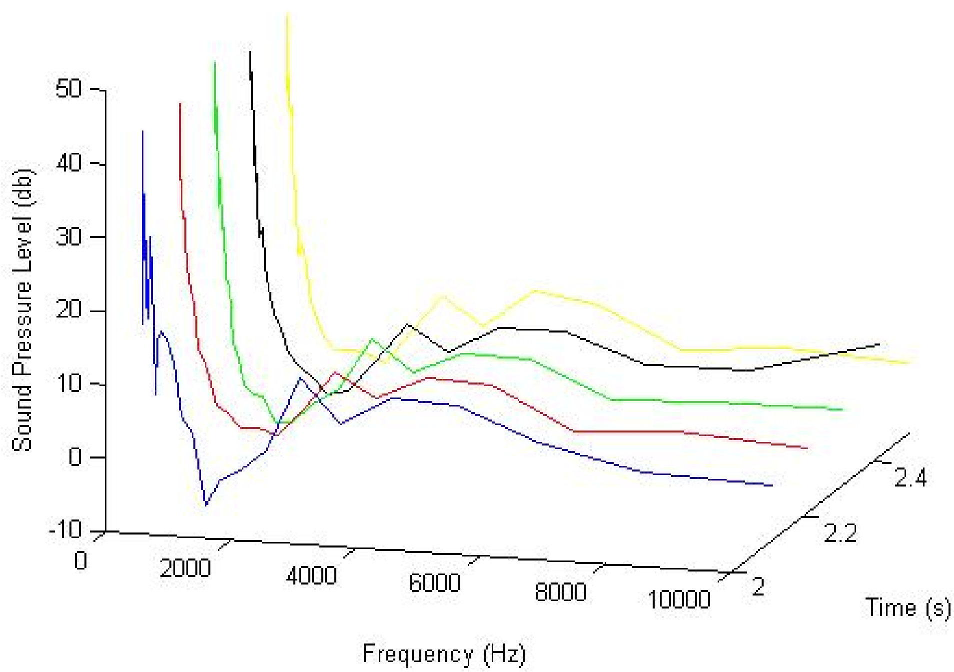

Figure 29. Frequency versus SPL Observations from Ambient Environment 1 Sound File for First 5 Time Observations

The 3,019 sound observations comprising Figure 29 are reduced to one overarching observation with 31 SPL values associated with the 31 frequency ranges as depicted in Figure 30. This reduction makes the comparison between helicopter stimulus SPL and ambient environment SPL more efficient because instead of having to compare these changing values at each of the thousands of observations, the comparison only needs to happen across 31 SPL values for each ambient environment recorded. Consequently, this makes model building of an aircraft acoustic probability of detection model building a much faster process. In this chapter, the SPLs associated with the 20th, 50th, and 80th quantiles of a number of ambient environments are created and displayed. The 20th, 50th, and 80th quantiles of the ambient sound environments were chosen (instead of just one quantile level) to provide an idea of how the variance of the SPL values of the data differs across the frequency range in each ambient environment. A more complete portion of the SPL data is displayed through these three quantile levels.

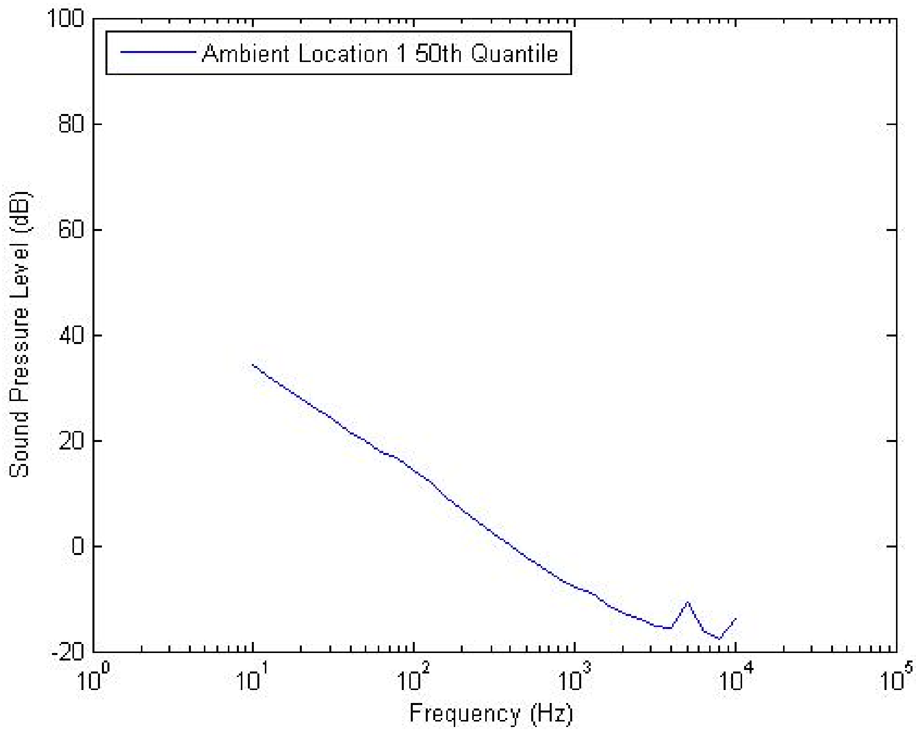

Figure 30. Ambient Environment 1 50th Quantile

Quantiles are found by taking the inverse of the cumulative distribution function (CDF) of a random variable. A quantile algorithm uses a value-based sorting of all the data in an array and then separates the sorted data into equal-sized subsets of data [19]. For the nine ambient environment datasets, each of the 31 columns of data are value-based sorted and the quantiles are determined. This process becomes computationally expensive when there are many large datasets with thousands of observations. After the nine ambient environment datasets were processed, using the quantile tool in Matlab, the datasets were broken up into arrays representing their 20th, 50th, and 80th quantiles. The 20th, 50th, and 80th quantiles from the 1st, 5th, and 9th ambient environements are displayed in Figures 31, 32, and 33, respectively.

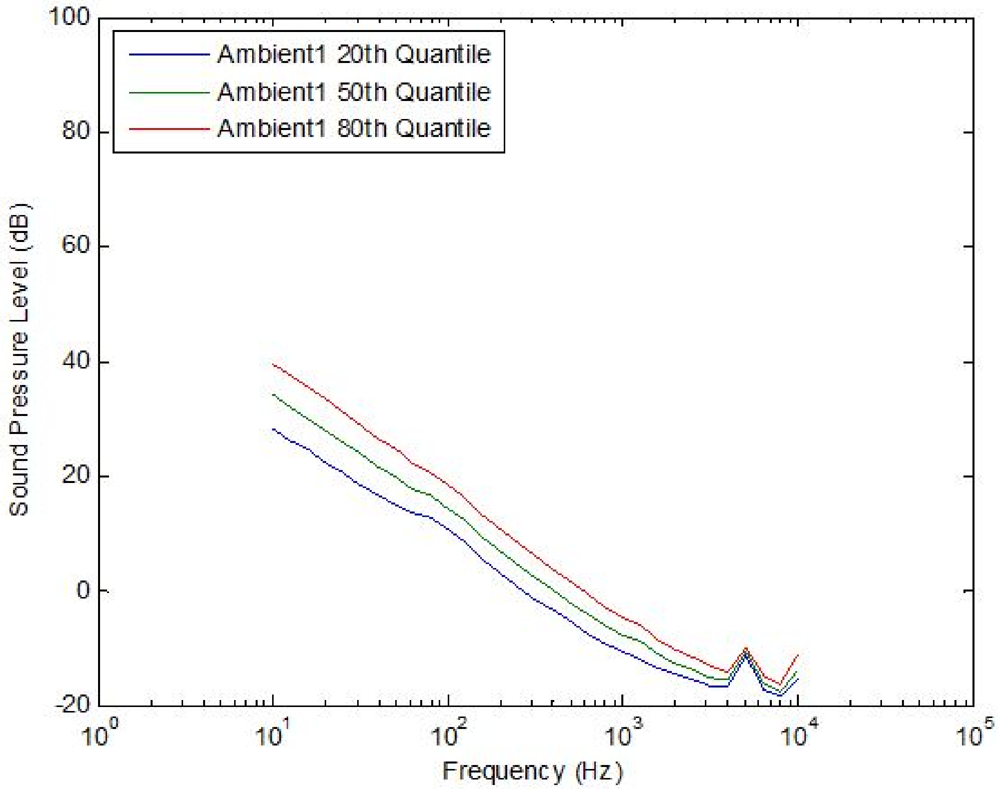

Figure 31. Ambient Environment 1 20th, 50th, and 80th Quantiles

Comparing Environments at Different Quantiles.

A plot of all nine ambient environments, at each of the 20th, 50th, and 80th quantile settings, are displayed in Figures 34, 35, and 36, respectively. These plots show the large range of differing sound pressure level values. The range of the SPLs associated with these nine ambient environments span approximately -20 to 60 decibels (dB). This large range indicates that predictive accuracy could be increased by including human detection probability data for aircraft at different ambient environments in an aircraft aural detection model.

An interesting relationship that emerges through the plotting of the quantile levels is the inverse relationship between frequency (Hz) and SPL (dB). This relationship

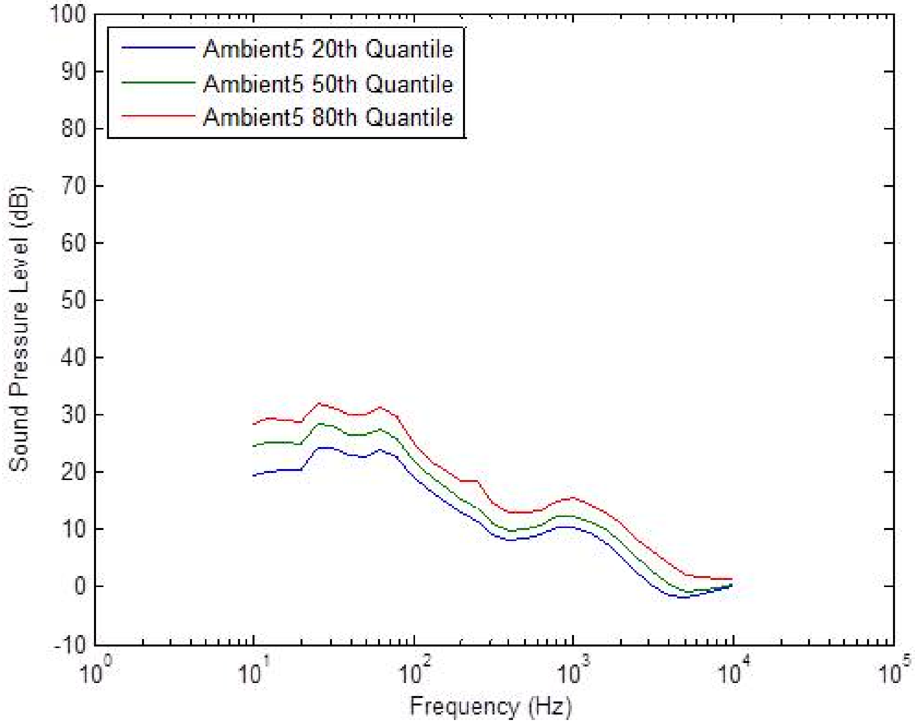

Figure 32. Ambient Environment 5 20th, 50th, and 80th Quantiles

holds true for all of the ambient environments except for the sixth one, which increases steeply around 7,000 Hz and then decreases steeply around 10,000 Hz. Another observation is that SPLs are quite variable depending on the type of environment in which they are measured. This implies that changing the ambient sound trace sample used in a model, based on an environment of interest, can potentially lead to significant improvements in a model's predictive capabilities. This idea is further discussed in Section 3.3.

Exploring the Distribution of the Ambient Data.

Histogram outputs of the SPL regressor data from the 31 frequency ranges of the 18 different probability of detection models from the logistic regression section of this chapter were created using JMP software to examine the underlying distribution of

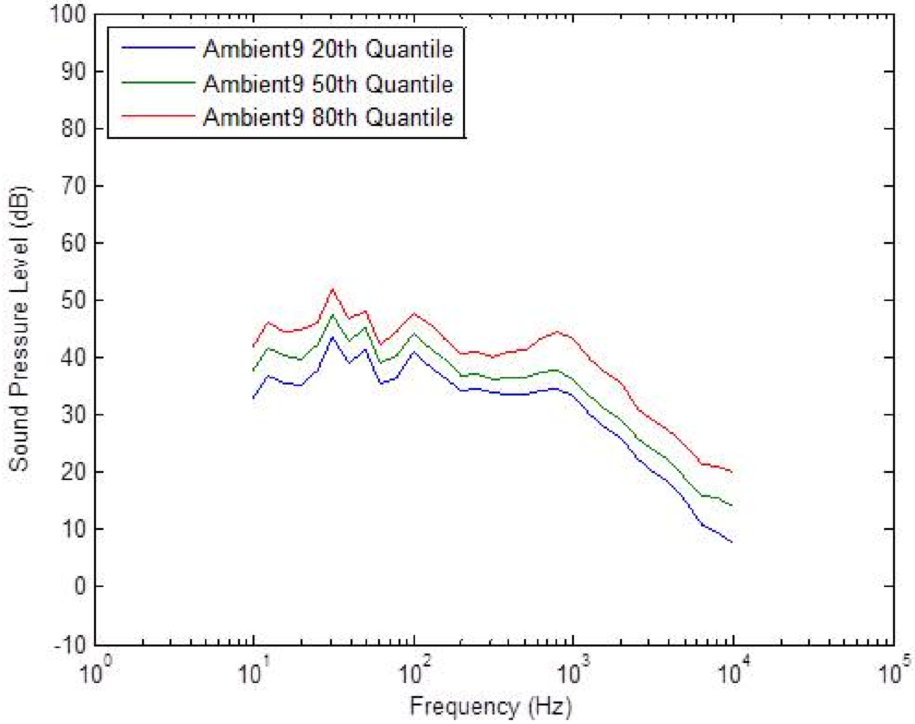

Figure 33. Ambient Environment 9 20th, 50th, and 80th Quantiles

the data. Understanding the underlying distribution of an ambient environment data set can prove very useful if the data follows a normal or symmetric distribution. If this is the case, only the SPL mean and standard deviation of an ambient environment need to be found to properly model an ambient environment in an aircraft probability of detection model. Furthermore, subject matter experts can aid the data collection process of model building by acquiring the SPL mean and standard deviation of an environment of interest before a model is built instead of model builders having to sit out in the field for days at a time recording thousands of ambient environment sound trace observations. Understanding the underlying distribution of the data can also lead to monetary savings during the data collection phase of model building. This knowledge can aid in determining the appropriate number of observations needed to maximize model validity, while minimizing experimental costs.

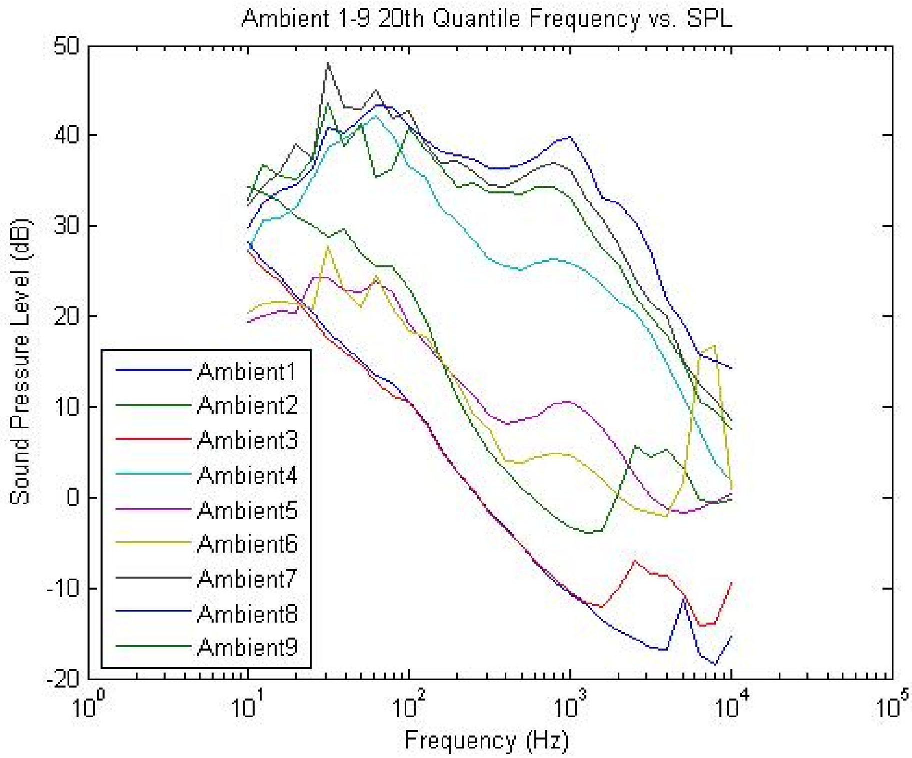

Figure 34. Ambient Environments 1-9 20th Percentile Frequency vs. SPL

Four of the histogram outputs from the 18 reduced probability of detection models are displayed in Figures 37, 38, 39, and 40. The remaining histogram outputs from the other 14 models created were not included due to size constraints. Applying these distribution based assumptions to the model building process yields computational efficiency by avoiding the data sorting. This is discussed further in sections 3.2 and 3.2. These symmetric and normal distribution-based methods explore how this sorting function used in the standard quantile algorithm can be altogether removed from the quantile process with little difference to the overall model.

Based on the four histogram figures depicting the distribution of four of the eighteen datasets, the data seems to quite closely follow a normal distribution, which is what we wanted to see. Therefore, incorporating the symmetric and normal distribution based assumptions seems to be an appropriate measure to increase computational

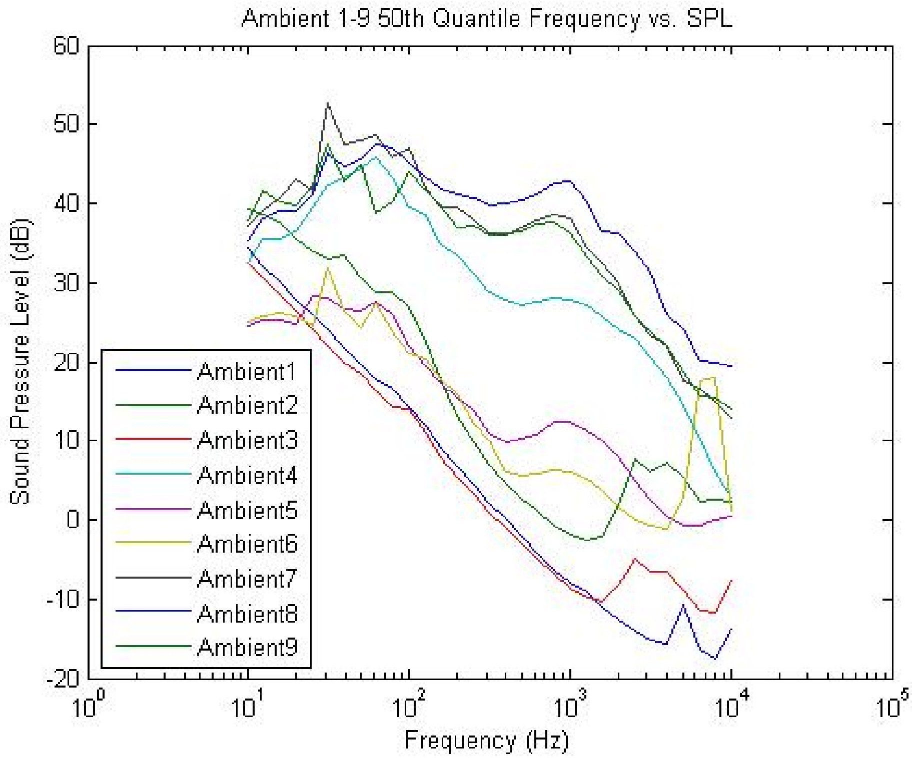

Figure 35. Ambient Environments 1-9 50th Percentile Frequency vs. SPL

efficiency and simplify acoustic data collection.

Symmetric Distribution Based Quantiles.

The next two subsections discuss how the symmetric and normal distribution-based assumptions can be incorporated into probability of detection modeling to decrease the computational demands caused by using sorting in a quantile method. The original quantile algorithm sorts the dataset placing the median value in the center of the array, which causes a lot of computational demands. If the data are assumed to follow a symmetric distribution, the mean is also the median of the data so no sorting is required, thereby decreasing the computational burden. Examples of the rectangular and half-circular symmetric distributions are displayed in Figures 41 and 42.

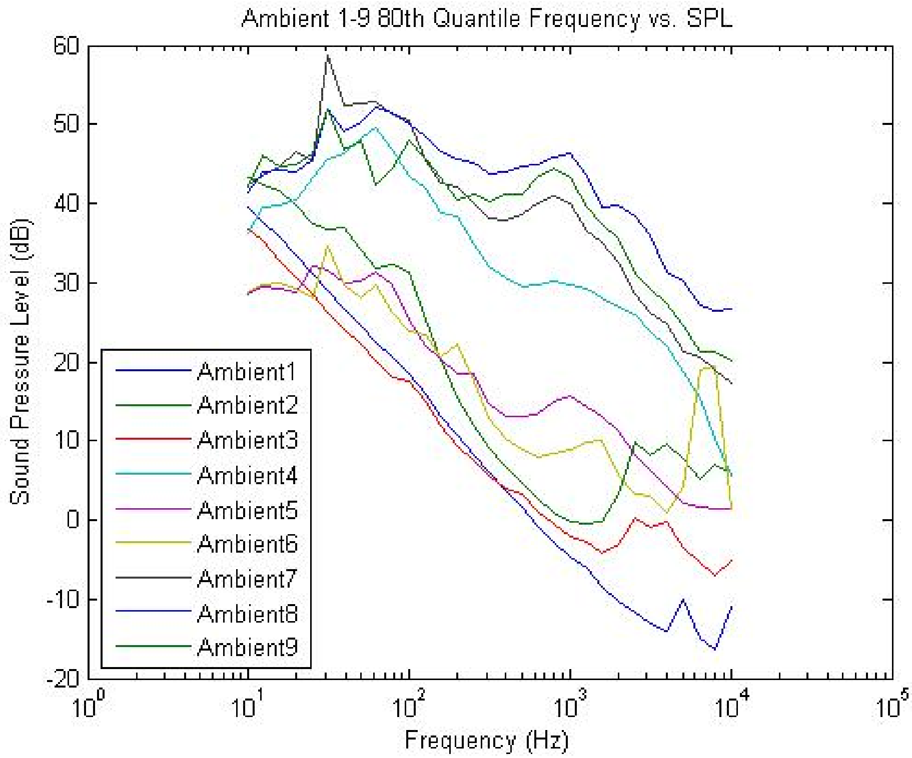

Figure 36. Ambient Environments 1-9 80th Percentile Frequency vs. SPL

Based on the histograms displayed earlier in the chapter, a triangular symmetric distribution based assumption was chosen to represent the ambient environment dataset. The three governing equations used to process the 9 different ambient environment datasets and find the 20th, 50th, and 80th quantiles using the symmetric distribution based assumptions can be seen in Equations (9), (10), and (11), respectively.

$$Sym(20) = (0.20 * (AmbSPL(max) - AmbSPL(min))) + AmbSPL(min) \tag{9}$$

$$Sym(50) = (0.50 * (AmbSPL(max) - AmbSPL(min))) + AmbSPL(min) \tag{10}$$

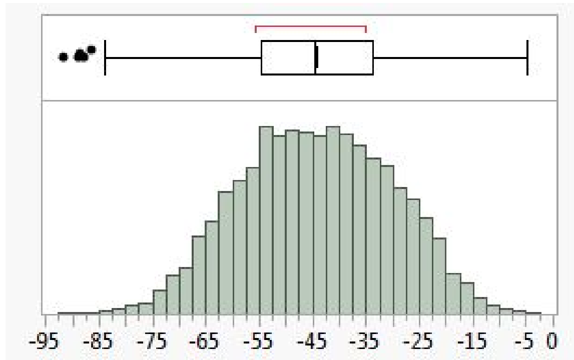

Figure 37. Histogram of Ambient Environment 1 Helicopter 2 Reduced Data

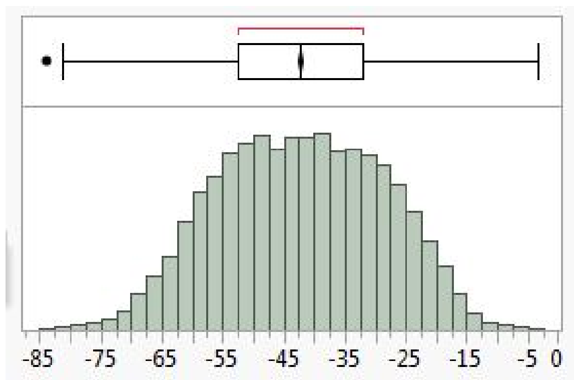

Figure 38. Histogram of Ambient Environment 3 Helicopter 2 Reduced Data

$$Sym(80) = (0.80 * (AmbSPL(max) - AmbSPL(min))) + AmbSPL(min) \quad (11)$$

Normal Distribution Based Quantiles.

As with the symmetric distribution, the normal distribution assumes the mean is the median and the data are symmetric about this mean. The form of the distribution is quite different however. These two distributions differs in the way that they represent the distribution of the data. An illustration of the normal distribution is displayed in Figure 43.

The normal distribution is incorporated into the quantile method using calculations involving the mean and standard deviation of the data. Since 68% of the

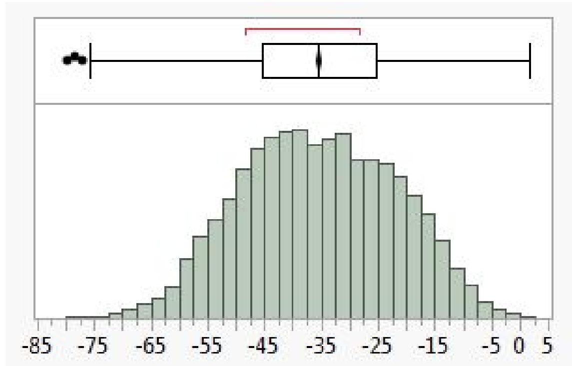

Figure 39. Histogram of Ambient Environment 5 Helicopter 2 Reduced Data

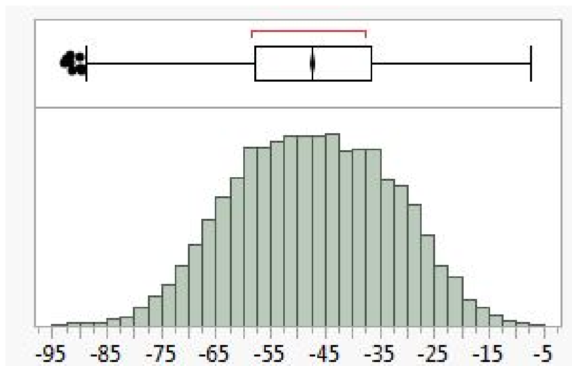

Figure 40. Histogram of Ambient Environment 7 Helicopter 1 Reduced Data

population falls within 1 standard deviation of the mean, then 60% of the population falls within 0.882 standard deviation of the mean. The 20th and 80th quantiles of each ambient environment dataset are found by multiplying 0.882 by 1 standard deviation of the population and subtracting it from and adding it to the population mean [3]. This means that knowledge of the mean and standard deviation of any ambient acoustic environment around the world yields an ambient sound profile of that environment resembling a quantile-based model requiring a full data set. Therefore, SMEs can sample these environments to estimate the approximate mean and standard deviation of the sound environment and this information can be incorporated into an aircraft probability of detection model quite rapidly.

The three governing equations used to process the 9 different ambient environment datasets and find the 20th, 50th, and 80th quantiles using the normal distribution

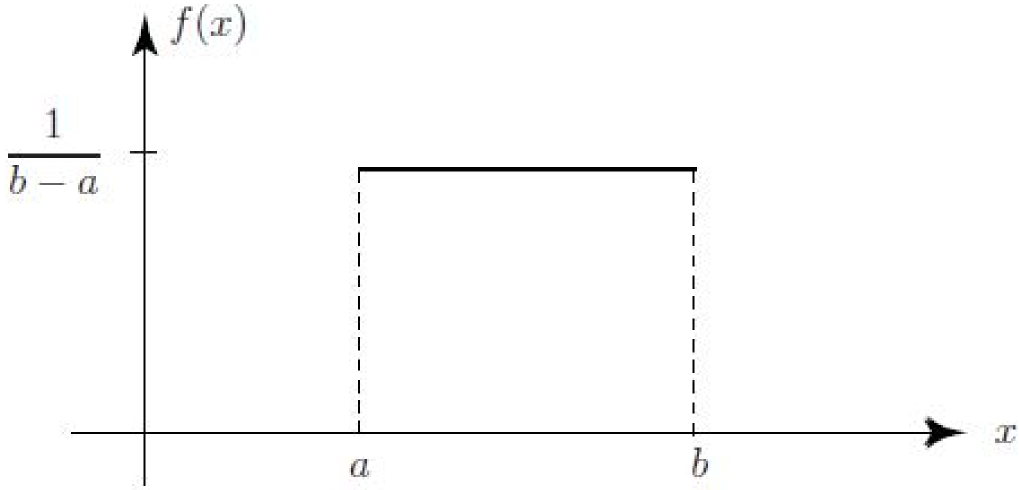

Figure 41. The Rectangular Symmetric Distribution [11]

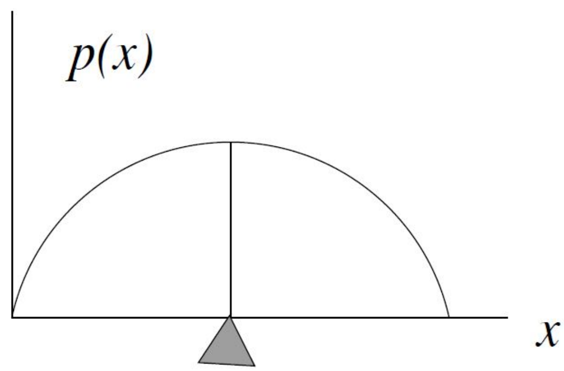

Figure 42. The Symmetric Probability Distribution Example [12]

based assumptions are in Equations (12), (13), and (14), respectively.

$$NormQuant(20) = ((AmbSPL(mean) - ((0.882 \times AmbSPL(stddev))) \qquad (12)$$

$$NormQuant(50) = AmbSPL(mean) \qquad (13)$$

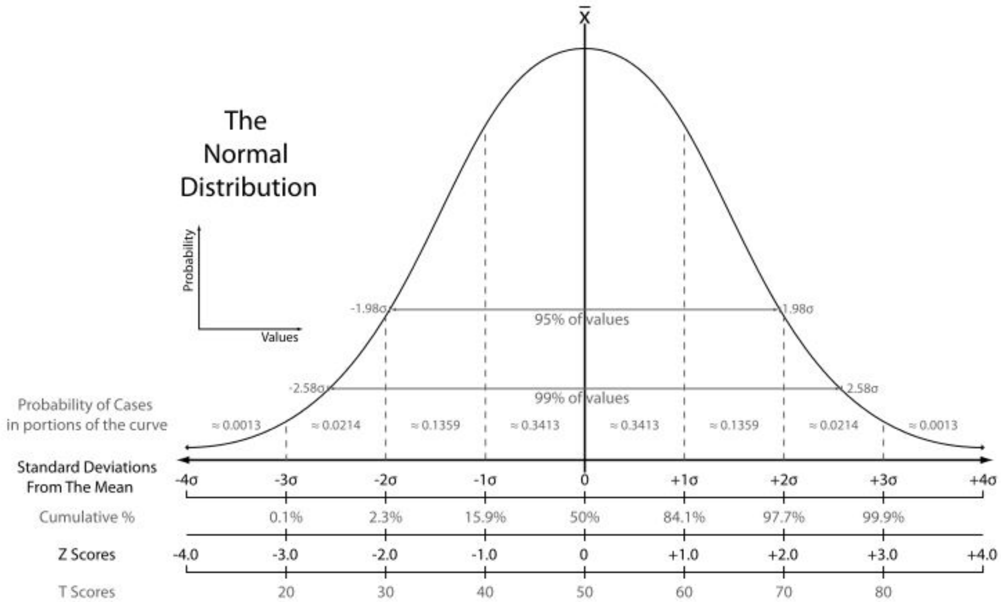

Figure 43. The Normal Distribution [13]

$$NormQuant(80) = ((AmbSPL(mean) + ((0.882 \times AmbSPL(stddev))) \qquad (14)$$

Comparing Performance of Standard, Symmetric, and Normal Quantiles.

Visual comparison of the standard, symmetric, and normal approaches to creating quantile based representations of the ambient sound environments are used to determine how much the three approaches differ. The performance of these approaches for the 20th quantiles associated with ambient environments 1, 5, and 9 are displayed in Figures 44, 45, and 46, respectively.

Based on these figures comparing the three different quantile approaches, the standard and normal quantile approaches yield the most similar SPL outputs, while the triangular symmetric approach is quite different across the frequency range. Knowing that the normal approach significantly outperforms the symmetric approach in terms

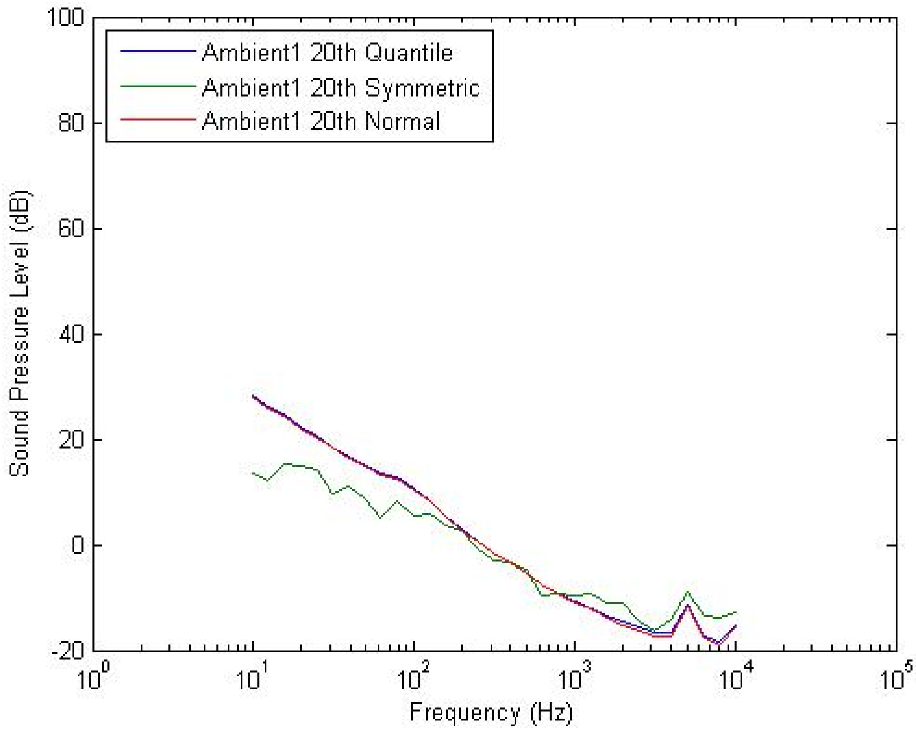

Figure 44. Standard, Symmetric, and Normal 20th Quantiles Ambient Environment 1

of how closely it resembles the standard approach used in the Matlab quantile function is important in terms of choosing which distribution should be used to increase computational efficiency and simplify data collection. To simplify data collection the mean and standard deviation of an ambient environment could be found by SMEs prior to model building and to increase computational efficiency, the normal distribution quantile approach could be used in lieu of the standard quantile approach. The next section discusses the matching function created to match an ambient sound profile from any possible environment to the most similar ambient sound profile from the human-based study.

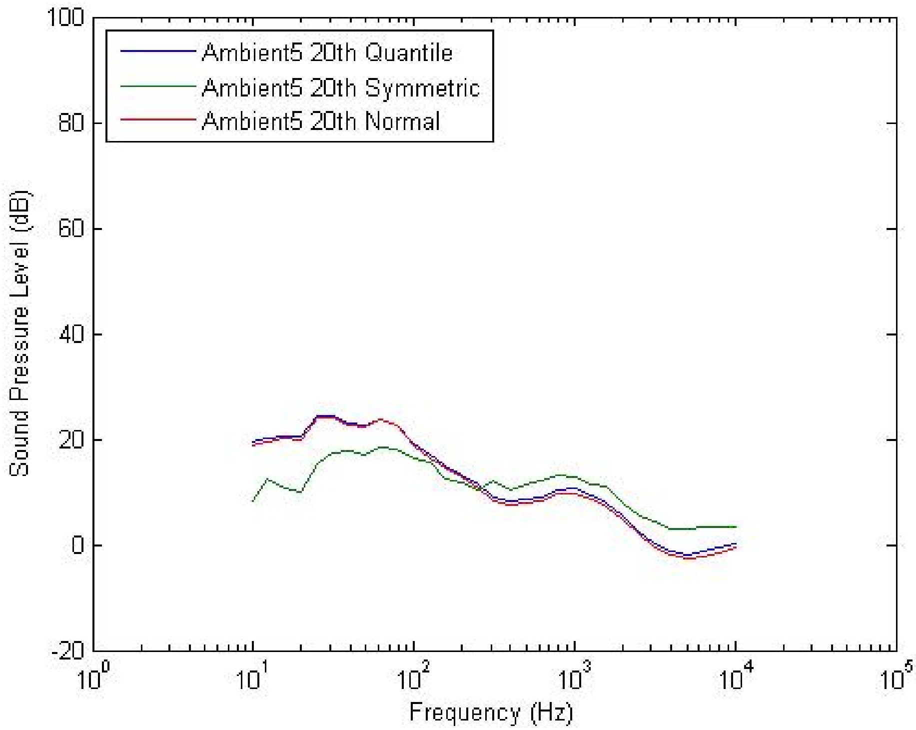

Figure 45. Standard, Symmetric, and Normal 20th Quantiles Ambient Environment 5

3.3 Creating an Ambient Environment Matching Function

Purpose of Function.

Simplifying assumptions are often made to reduce complexity and computational time associated with model calculations. However, it can be beneficial to consider the tradeoff between model validity and efficiency when it comes to these simplifying assumptions. In terms of acoustical ambient sound profiles, simplifying assumptions can occur in terms of the number of ambient sound profiles to include in a model. When only one ambient sound environment is used to gain insight regarding whether or not a human or device on the ground is able to identify the acoustical signature of an aircraft in any ambient environment around the world, the computational speed needed for ambient environment data processing is severely reduced. However, when multiple ambient environments are used to find the probability that a human or device

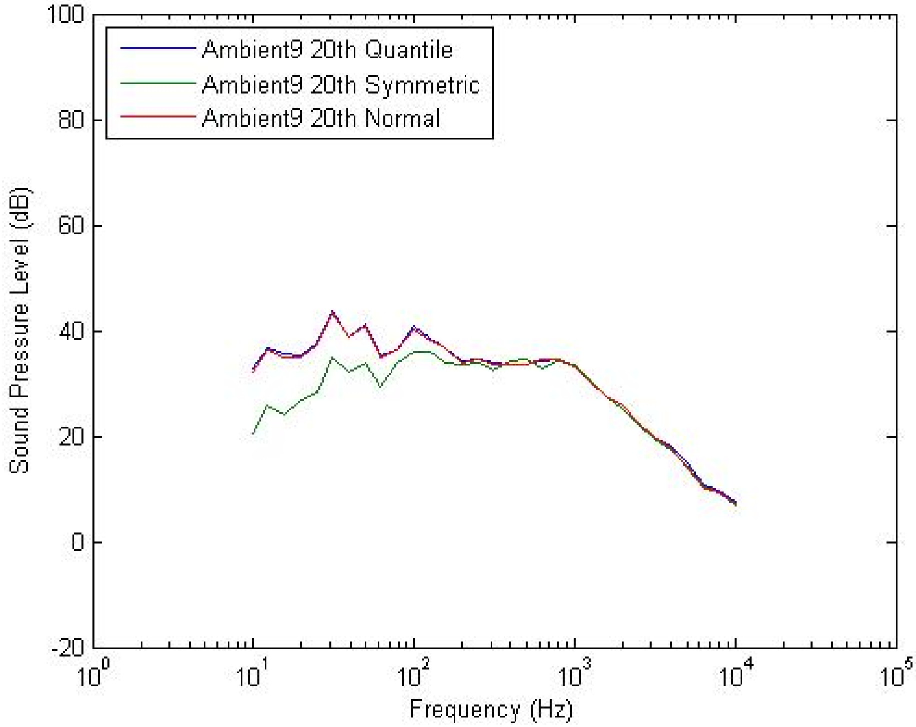

Figure 46. Standard, Symmetric, and Normal 20th Quantiles Ambient Environment 9

on the ground is able to identify the acoustic impression of a machine, the validity of the model will increase if the ambient environment that the ground receiver is listening in is more accurately represented by a similar ambient environment sound trace in the model.

For example, if the probability that a ground receiver can identify the acoustical signature of a machine from the acoustical signature of the surrounding environment is calculated using a sample sound trace from a rural ambient setting and the receiver is actually located in a urban setting, where the associated sound pressure levels are much higher than a rural setting, then the model predictions for probability of detection are reduced in fidelity. In effect, the model would indicate a higher probability of detection than the true probability of detection because the ambient environment is represented by a sound profile that has lower SPLs than in actuality.

On the contrary, if the model bases its predicted response values for probability of detection based on an urban environment sound trace sample, but the receiver is actually located in a rural environment than the model would indicate a lower probability of detection than the true probability of detection. This tradeoff between computational efficiency and model validity should be considered when building an acoustic model where ambient noise is included and can lead to increased model fidelity, if included appropriately.

There are also disadvantages associated with collecting too much data including the cost of data collection (in terms of time and money) and the computational demands that would occur if model builders attempted to collect acoustical signatures from thousands of different possible ambient sound environments around the world. The model builder in conjunction with the decision maker must agree on the appropriate number of ambient environments necessary to properly represent the types of operating environments for the aircraft. However, the problem of overcollection of data in acoustic detection model building does not seem to be an issue since few human-based acoustic detection experiments had been done before Hoglund *et al.* performed their research.

Hoglund *et al.* (2008), discusses how little data has actually been collected concerning human processing of in-flight aircraft generated SPLs radiated to listening positions on the ground. Hoglund states that despite the large number of models developed to predict aircraft aural detection by ground listeners, "one of the difficulties presented by all the models reported is a lack of corroboration by empirical data from human listeners" [1]. In this way, the human-based data collected by Hoglund and used in this research is quite revolutionary and can be used to increase the fidelity of aural detection models.

One of the ways that this research approaches increasing the fidelity of these types of aural detection models is by creating a function using the Matlab programming language that makes it possible to input an ambient sound profile from any sound environment in the world and find the closest matching environment dataset from the nine ambient environments that Hoglund *et al.* collected. This will insure that the fidelity associated with an aircraft probability of detection model is not lost when the aircraft is operating in a rural, urban, or suburban environment among others. Although incorporating this function into a model could decrease the computational efficiency of the model, we believe that the fidelity gained by the increased ambient environment flexibility outweighs the computational demands needed to incorporate it.

Matching Function.

Using the nine ambient sound trace datasets provided, a Matlab function based on the sum of squared errors (SSE) equation was created to match a random ambient environment sound trace with its closest match from the human-based study. In this function, the 31 20th quantile SPL data points from a random ambient envrionment sound trace are compared to the 31 20th quantile SPL data points across the nine ambient sound environments. The 20th quantile was selected over the 50th or 80th quantile based on insight received from our sponsors regarding the quantile setting they were most interested in looking at. This comparison helps to identify which of the nine ambient acoustic signatures best match with the random ambient sound trace. Once this is determined, the associated data from the closest matching ambient sound environment can be included in the model to determine the probability that a human listener will be able to hear a stimulus. The goal of this function is to increase model validity by removing the assumption that all ambient sound environments are the same, which is not the case. The governing equation based on the SSE formula that helped select the closest ambient environment from the nine environments available, with $\hat{y}_i$ representing the SPLs of the unknown ambient environment at each of the 31 human auditory frequency ranges and y_i representing the SPLs at each of the 31 frequency ranges of one of the nine previously recorded ambient environments is listed in Equation (15).

$$\sum_{i=1}^{31} (\hat{y}_i - y_i)^2 \tag{15}$$

The human-based ambient dataset that has the smallest sum of squares compared to the random ambient dataset is selected to create the new probability of detection model. The function then produces a bar graph in Matlab to give the user a visual image that indicates why a specific ambient environment was chosen. The ambient environment associated with the lowest value for SSE, or the smallest bar in the bar graph, is chosen as the dataset to represent the unknown ambient environment. Three of these bar graphs can be seen in Figure 47, Figure 48, and Figure 49.

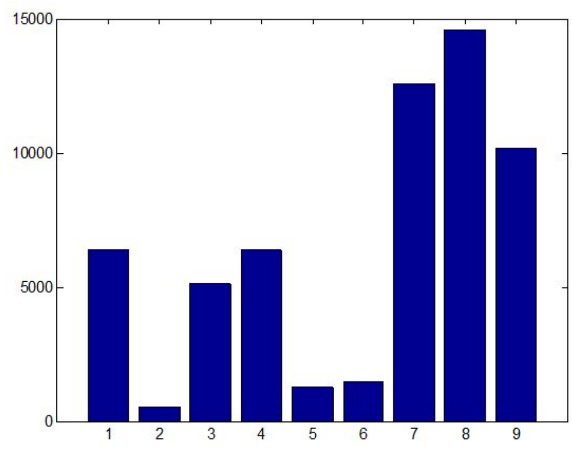

Figure 47. Matching Function Where Ambient Environment 2 is Chosen

As seen in Figure 47, the probability of detection associated with ambient environ-

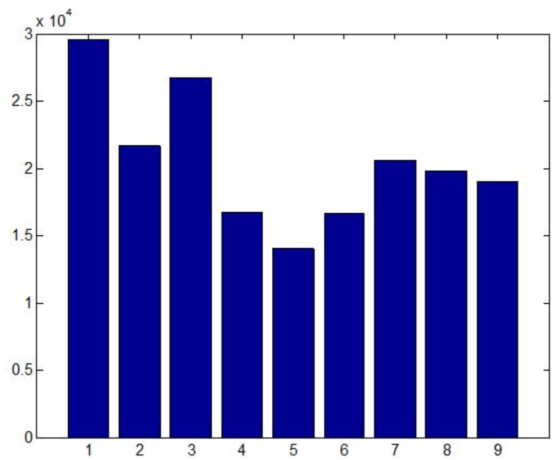

Figure 48. Matching Function Where Ambient Environment 5 is Chosen

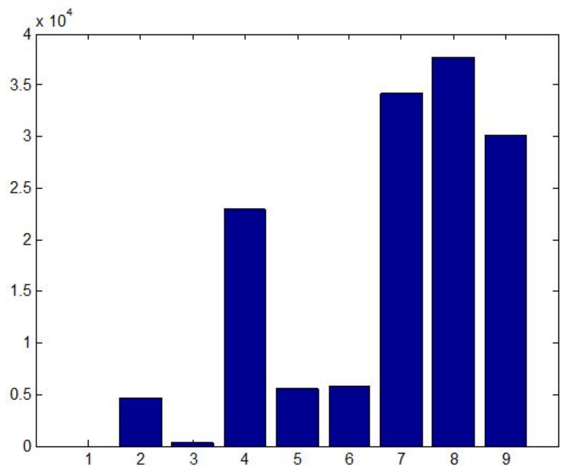

Figure 49. Matching Function Comparing Ambient Environment 1 with Known Ambient Environments

ment 5 ('Suburbancorr') would be chosen to represent this environment. As seen in Figure 48, the probability of detection associated with ambient environment 2 ('Ambient5') would be chosen to represent this environment. As seen in Figure 48, the probability of detection associated with ambient environment 1 ('Ambient19') would be chosen to represent this environment, which makes sense because for this output because ambient environment 1 was compared to all nine of the existing ambient environments. Therefore, this dataset input should be a perfect match when compared to the same environment that it represents.

The matching function created in this research was tested using 25 different random ambient sound environments. The results of these matching tests in terms of the ambient environment from the human-based study that matched closest with the random ambient environment sound trace file can be seen in 4. This function employs only one of a vast number of the possible matching methods that could be used to determine which of the nine ambient environments should be selected and matched with a random ambient environment of interest. It would be interesting to complete further research regarding the best matching method for acoustical ambient environment data. Although the matching method used in this function represents a small portion of possible matching methods, it is still very useful when it comes to probability of detection model building and should be considered to increase model fidelity of existing models.

Table 4. Random Ambient Environments Matched to Hoglund *et al.* **(2008) Ambient Environments**

Random File	File Name	Match
1	Ambient1	Ambient5
2	Ambient2	Ambient5
3	Ambient3	Ambient5
4	Ambient4	Ambient28
5	Ambient6	Ambient19
6	Ambient7	Ambient19
7	Ambient8	Ambient28
8	Ambient9	Ambient28
9	Ambient10	Ambient28
10	Ambient11	Ambient28
11	Ambient12	Ambient28
12	Ambient13	Ambient28
13	Ambient14	Suburbancorr
14	Ambient15	Ambient19
15	Ambient16	Ambient19
16	Ambient17	Ambient19
17	Ambient18	Ambient19
18	Ambient20	Ambient19
19	Ambient21	Ambient19
20	Ambient22	Ambient19
21	Ambient23	Ambient19
22	Ambient24	Ambient28
23	Ambient25	Ambient28
24	Ambient26	Ambient28
25	Ambient27	Ambient28

IV. Conclusion

4.1 Overview

The research conducted during this thesis addressed three different areas in the field of aircraft acoustics. These areas included logistic regression modeling of aircraft probability of detection models, the application of distribution-based assumptions to data collection and processing techniques, and function building which enables the Hoglund *et al.* (2008) human-based data findings to be applied to any ambient sound environment around the world. In the logistic regression modeling portion of this research, the Hoglund *et al.* (2008) dataset was used to create 18 environment-specific aircraft probability of detection models. These models made it possible to predict the probability that a helicopter will be detected by a ground listener in the environment based on the difference between the helicopter and ambient environment SPLs. Furthermore, these models can be used to predict helicopter probability of detection in similar ambient sound environments to the rural, urban, and suburban environments studied.

In the underlying distribution-based assumptions portion of this research, the distributions of the 18 environment-specific datasets were examined to determine whether the symmetric or normal distributions properties could be used to replace computationally expensive attributes of the quantile function used in Matlab. Through this research we found that the assumptions from the symmetric and normal distributions could be applied to the 18 datasets as well as the fact that the normal distribution was a better fit for the data than the triangular symmetric distribution. Another important finding that was gained through the distribution-based research portion of this thesis was that since the data followed the normal distribution so closely, the data collection phase for probability of detection modeling could be made much more efficient by hiring SMEs to collect the mean and standard deviation of an ambient sound environment at the 31 different frequency levels. This knowledge could then be used to create a plot that resembles the underlying SPL make up of this environment, which would make it possible to predict aircraft probability of detection through SPL comparison as well as match this ambient sound environment with a similar environment that has human-based data for it.

In the last area portion of the research conducted during this thesis, an ambient environment matching function was created in Matlab coding language which matches any possible ambient sound environment in the world to the ambient environment that it most closely resembles out of the 9 ambient environments recorded during the Hoglund et al. (2008) study. This research was geared towards increasing the understanding of the data set and fidelity of probability of detection models for fixed-wing and rotary-wing aircraft.

This research has been successful in improving the understanding of aircraft acoustic modeling, the understanding of the distribution of data in acoustic modeling, and the importance of ambient sound environments in a model. However, there is still much research to be done and many areas to improve the research recounted throughout this thesis. One of these areas of improvement relating to logistic regression modeling includes the ability to verify and validate the logistic regression models created as well as determining the most parsimonious model through examining different combinations of the 31 regressors and determining whether or not any of the model assumptions were violated. Another area of improvement relating to the matching function built in Matlab has to do with looking at a wide variety of matching algorithms in order to find the best way to match random ambient sound environment with one from the Hoglund data. It would be interesting to see what types of algorithms would be most suitable for this job as well as comparing their performance through various metrics (speed, validity, etc.). By improving the understanding of various aspects of aircraft acoustics we have helped to increase the validity of aircraft probability of detection modeling and through this have had a positive effect on military aircraft operational effectiveness.

CHARACTERIZING AND CLASSIFYING ACOUSTICAL AMBIENT SOUND PROFILES

2d Lt Paul Gaski
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INTRODUCTION

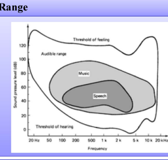
Acoustical modeling focuses on the sound pressures generated by the operation of some system of interest, the propagation of the sound through some medium (the atmosphere) and the sound pressure levels picked up by the receiver (listening device or a human). Ambient noise, or the background noise occurring naturally in an environment, affects the ability of the receiver to identify the sound from the system of interest. This work examines nominal logistic modeling of human performance data, methods to remove the time-dependency aspect of ambient sound profiles, and develops a method with which to classify sample ambient noise profiles against one of nine standard ambient noise profiles.

RESEARCH OBJECTIVES

- Create probability of detection models using nominal logistic regression
- Use quantiles to create various sound profiles of ambient environments
- Analyze alternative methods for creating ambient environment sound profiles
- Create ambient matching function to match random ambient environment sound trace data to existing data with human-responses

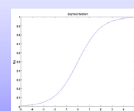
Human Hearing Range

- Human hearing range is limited
- Hearing performance increases as frequency increases
- Aircraft emit frequency throughout the entire frequency spectrum at various sound pressure levels (SPLs)

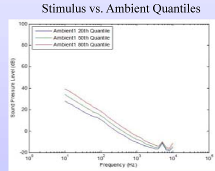


Nominal Logistic Regression

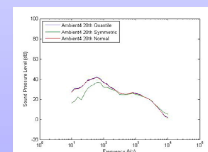
- Sigmoid function is the basis of nominal logistic regression (Logit Regression)
- 18 probability of detection models created using nominal logistic regression
- Indicate key frequencies where aircraft is most vulnerable to human detection



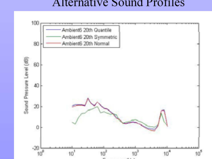
Stimulus vs. Ambient Quantiles



Alternative Sound Profiles



Alternative Sound Profiles



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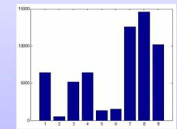
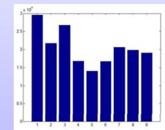
Ambient Matching Function

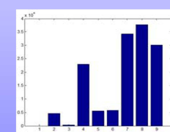
Random Ambient 1



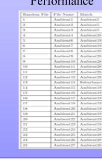
Random Ambient 1



Random Ambient 1



Performance



RESULTS

- 18 probability of detection models pivotal in identifying key frequencies where human aural detection of aircraft is highest
- Probability of detection models can also give insight to aircraft detection in similar ambient environments (rural, urban, and suburban)
- Quantile analysis created sound profile of ambient environments and identified normal distribution as best alternative to quantile algorithm
- Ambient matching function useful in matching random ambient environments with ambient environments with human response data

FUTURE RESEARCH

- Use neural networks to create higher fidelity aircraft probability of detection models
- Use acoustic profiles built with normal distribution to create more efficient data collection process
- Compare performance of matching algorithm used in matching function to other known matching algorithms

DEPARTMENT OF OPERATIONAL SCIENCES

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14. ABSTRACT

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15. SUBJECT TERMS

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